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# ESSAYS ON DETERMINANTS OF FINANCIAL BEHAVIOR OF INDIVIDUALS

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*To Aleksander*

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## Executive Summary

This thesis investigates the role of individual-specific factors in individuals' financial behavior. The main focus of the analysis is on two characteristics of individuals: risk attitude and gender. Although these two factors are believed to be important determinants of financial behavior, a review of literature reveals that many questions regarding their role remain unresolved. This thesis aims at closing the gaps in the literature by providing empirical evidence on the effects of risk attitude and gender on various aspects of financial behavior.

The thesis consists of four studies addressing the following questions: 1) Do individual risk attitudes affect the decision makers' propensity to diversify their portfolio of financial assets? 2) Does gender affect the probability of investing in risky financial assets and the share of wealth allocated to these assets? 3) Conditional on investing in risky financial assets, do males take bigger risks than females? 4) Does gender determine the chances to get funds in credit markets? Evidence on these questions is provided using two different data sources. Firstly, a part of the analysis relies on the data collected through representative national surveys of household finances (German Socioeconomic Panel, Austrian Survey of Household Financial Wealth, Dutch Household Survey, Italian Survey of Household Income and Wealth, Spanish Survey of Household Finances). Advantages of the survey data include the data representativeness for population of the studied countries, the wide range of surveyed individual characteristics, and the comparability of the data across countries. Secondly, a part of analysis in the thesis is conducted using observational data collected by the author from an Internet-based marketplace for peer-to-peer lending. Peer-to-peer lending is a financial innovation consisting in direct lending and borrowing among individuals without intermediation of financial institutions. An advantage of using these data is that they include detailed information about the main characteristics of investments which are not available in the survey data, for instance, expected and realized returns to investments. These data also provide evidence on the behavior involving innovative financial products and allow exploring whether impact of individual factors in direct financial relationships differs from intermediated relationships.

***Keywords***: consumer finance, investment choices, portfolio composition, access to credit, risk-taking, gender, qualitative choice models, Heckman's sample-selection correction

# Zusammenfassung

Die vorliegende Dissertation befasst sich mit der Frage, inwiefern das Finanzverhalten von Individuen von ihren persönlichen Eigenschaften abhängt. Im Zentrum der Analyse stehen zwei Eigenschaften: persönliche Risikoeinstellung und Geschlecht. Obwohl beide Eigenschaften als wichtige Einflussfaktoren des Finanzverhaltens angesehen werden, sind viele Fragen bezüglich ihrer Rolle noch offen. Diese Dissertation beschäftigt sich mit den offenen Fragen und liefert empirische Evidenz hinsichtlich der Relevanz von Risikoeinstellung und Geschlecht für verschiedene Aspekte des Finanzverhaltens.

Die Dissertation besteht aus vier Studien, die sich mit den folgenden Fragen beschäftigen: 1) Welchen Einfluss hat die persönliche Risikoeinstellung der Investoren auf ihre Entscheidungen hinsichtlich der Diversifizierung von Finanzportfolios? 2) Hängt die Wahrscheinlichkeit in risikobehaftete Anlagen zu investieren und das Portfolioanteil dieser Anlagen vom Geschlecht der Investoren ab? 3) Wenn eine Investition in risikobehaftete Anlagen vorgenommen wird, hängt der Grad des eingegangenen Risikos vom Geschlecht der Investoren ab? 4) Spielt das Geschlecht eine Rolle für den Zugang zu Finanzmitteln auf den Kreditmärkten? Um diese Fragen zu beantworten, werden zwei verschiedene Datensätze mit Hilfe von unterschiedlichen ökonometrischen Methoden analysiert. Der erste Datensatz erschließt Befragungsdaten, die durch repräsentative nationale Erhebungen von Finanzen privater Haushalte aufgenommen wurden (Deutsches Sozio-ökonomisches Panel (SOEP), Austrian Survey of Household Financial Wealth, Dutch Household Survey, Italian Survey of Household Income and Wealth, Spanish Survey of Household Finances). Zu den Vorteilen dieser Daten gehören unter anderem die Repräsentativität für die Bevölkerung eines Landes, das breite Spektrum der erfassten sozioökonomischen und demographischen Daten, und die Vergleichbarkeit der Daten zwischen den Ländern. Der zweite Datensatz besteht aus Beobachtungsdaten, die die Autorin auf dem Deutschen Internetmarkt für Peer-to-Peer Kredite gesammelt hat. Peer-to-Peer Kredite stellen eine innovative Form der Kreditvergabe dar und bedeuten direkte Leihung von Geld zwischen Privatpersonen ohne die Intermediation einer Bank. Ein wichtiger Vorteil solcher Daten besteht darin, dass sie Informationen über die erwarteten und realisierten Renditen der Investitionen enthalten, was für die genaue Bewertung des Risikoverhaltens von entscheidender Bedeutung ist.

***Keywords***: Finanzen privater Haushalte, Anlageentscheidungen, Portfolioauswahl, Zugang zu Krediten, Risikobereitschaft, Geschlechterdimension, Modelle mit qualitativen abhängigen Variablen, Modelle mit Sample-Selection

# Chapter 1

# Introduction

The continuously increasing participation of consumers in the financial markets[1], together with an increasing complexity of these markets, is prompting regulators and practitioners to investigate the determinants of financial behavior of individuals. Academic research is seeking to generate knowledge about the financial behavior that will help governments and financial institutions develop sound financial counseling of individuals. Effective counseling on questions related to financial markets can improve individuals' financial management and ultimately contribute to the overall stability of financial markets.

Research on individuals' financial behavior encompasses a wide range of theoretical and empirical studies investigating how individuals use financial markets and what factors determine their behavior. Investing and borrowing are the two main aspects of behavior associated with the usage of financial markets. Investing takes many forms ranging from saving for retirement to gambling with high-risk financial securities. Borrowing encompasses decisions on credit-card debt, mortgages, consumer credit and business loans. Although investing and borrowing are two distinct types of financial behavior, they are tightly interconnected and affect each other (Haliassos and Hassapis, 2002; Cocco et al., 2005; Davis et al., 2006). Determinants of investing and borrowing decisions comprise environmental and individual-specific factors. Environmental factors include but are not limited to development of financial markets, macroeconomic conditions, culture and social norms. Individual-specific factors are personal characteristics of decision-makers. They include various socioeconomic characteristics (e.g., wealth, income, education), demographic attributes (e.g., age, gender, health) and attitudinal factors (e.g., attitude towards risk-taking, trust, social openness etc.)

This thesis investigates the role of individual-specific factors in individuals' investing and borrowing behavior. Specifically, the analysis focuses on two characteristics of individuals: risk attitude and gender. Since most financial decisions involve risk-taking, risk attitude is a crucial characteristic of decision-makers that affects their choices (Wärneryd,

[1] Guiso et al. (2002, 2003); Ynesta (2008)

1996; Schooley and Worden, 1996; Donkers and van Soest, 1999; Fellner and Maciejovsky, 2007). Investigating the role of risk attitude in financial behavior should help improving our knowledge of the heterogeneity of behavioral patterns in the population. Gender is believed to influence individuals' propensity to take risk (Hartog et al., 2002; Hallahan et al., 2004; Fellner and Maciejovsky, 2007; Eckel and Grossman, 2008). Hence, this demographic characteristic deserves a closer consideration as a determinant of financial behavior.

The aim of the thesis is to answer the question: How do risk attitude and gender affect financial behavior? Because financial behavior takes a bewildering variety of forms, it is not feasible to cover them all within the scope of one dissertation. For this reason, this work is confined to a few aspects of investment and borrowing. These aspects include: (1) diversification of financial portfolios, (2) ownership and portfolio share of risky financial assets, (2) extent of risk-taking when investing in risky financial assets and (4) access to funds in credit markets.

The thesis contributes to the literature by providing empirical evidence on the determinants of financial behavior using two different data sources. Firstly, a part of the analysis relies on the data collected through representative national surveys of household finances (German Socioeconomic Panel, Austrian Survey of Household Financial Wealth, Dutch Household Survey, Italian Survey of Household Income and Wealth, Spanish Survey of Household Finances). Advantages of survey data include the data representativeness for population of the studied countries, the wide range of surveyed individual characteristics, and the comparability of the data across countries. Secondly, a part of analysis in the thesis is conducted using observational data collected by the author at an Internet-based marketplace for peer-to-peer lending. Peer-to-peer lending is a financial innovation consisting in direct lending and borrowing among individuals without intermediation of financial institutions. Advantages of using these data is that they provide evidence on the behavior involving innovative financial products and allow exploring whether impact of individual factors in direct financial relationships differs from what is reported in the literature on intermediated relationships.

The remainder of the introductory chapter is organized as follows. Section 1.1 provides an overview of the state of the academic research on the role of the risk attitude and gender in the financial behavior of individuals. Section 1.2 outlines the research questions addressed in the thesis and highlights the main findings.

## 1.1 Risk Attitude and Gender as Determinants of Financial Behavior

Since almost every financial decision involves some degree of uncertainty in the outcomes, financial behavior generally presents a risky behavior. Accordingly, the notion of individual attitude towards financial risks takes a central place in the literature. Attitude towards financial risks can be viewed as a personal trait that determines how much risk an individual is willing to accept when making financial choices. Researchers learn individuals' risk attitude by either eliciting it from the observed behavior of individuals or by directly asking individuals about how willing they are to take risks when making financial decisions (Dohmen et al., 2005).

One of the main questions studied in the literature, is how personal risk attitude affects actual financial behavior. Theoretical models describing the financial behavior view risk attitude as the main determinant of financial choices. For instance, the capital asset pricing model (CAPM) predicts that the degree of risk aversion determines what proportion of wealth an investor will allocate to risky financial assets. Empirical studies confirm this prediction. For instance, the portfolio fraction of risky assets is found to increase with individual willingness to take risks (Schooley and Worden, 1996; Wärneryd, 1996; Sunden and Surette, 1998).

However, not all the predictions of theoretical models regarding the relationship between the risk attitude and the financial choices are confirmed by the literature. For instance, despite the prediction of CAPM that risk attitude should not affect the level of diversification of a financial portfolio, there are theoretical studies arguing that risk attitude can play a significant role in how many assets are held in a financial portfolio (Campbell et al., 2003; Gomes and Michaelides, 2005). Yet, empirical evidence on the relationship between risk attitude and diversification decision is practically unavailable.

Another issue attracting attention in the academic literature is the question about what factors determine individual risk attitudes. Empirical studies provide strong evidence that risk attitudes vary with individual wealth, income, education and age. The role of a number of other factors is still unclear. For instance, despite the popular belief that gender is strongly correlated with the propensity to take financial risks, the literature provides mixed evidence regarding this relationship.[2] In particular, a large number of studies, which rely on surveys of financial behavior or laboratory experiments, show that females are significantly less inclined to take financial risks than males (Jianakoplos and Bernasek, 1998; Sunden and Surette, 1998; Bernasek and Shwiff, 2001; Hartog et al., 2002; Hallahan et al., 2004; Dohmen et al., 2005; Fellner and Maciejovsky, 2007).

In contrast, empirical studies focusing on professionally trained investors, like managers of investment funds, find that the behavior of males and females differs in minor ways or not at all (Johnson and Powell, 1994; Atkinson et al., 2003; Beckmann and Menkhoff, 2008). There are also some notable exceptions among the experimental studies. Specifically, Schubert et al. (1999) find that risk propensity of males and females depends strongly on whether experiments involve abstract gambles or contextually framed lotteries. In the latter setting,

[2] Croson and Gneezy (2009) provide a concise overview of this evidence.

females and males do not exhibit significant differences in risk propensity. Interesting evidence is provided by Holt and Laury (2002), who show that the effect of gender varies with the level of payoff. Females are more risk averse than males when lotteries involve low payoffs. However, when lotteries involve high payoffs, no differences between males and females are documented. Tanaka et al. (2010) find no effects of gender on the individuals' risk preferences. Finucane et al. (2000) and Booth and Nolen (2009) show that the role of gender in the propensity for risk taking varies depending on the cultural environment. Thus, so far the literature is inconclusive regarding the significance of gender differences in the financial risk-taking.

Regarding the reasons for gender differences in financial risk-taking, the literature offers a range of conjectures related to gender inequalities in wealth, labor income, social roles and access to credit Bajtelsmit and Bernasek (1996). The latter is particularly important, as discrimination in credit markets means that the discriminated individuals face more borrowing constraints than the other groups of borrowers. Tighter borrowing constraints have, in turn, important implications for investment behavior. For instance, as borrowing helps individuals smooth the level of consumption over the life-cycle (Gourinchas and Parker, 2002; Gross and Souleles, 2002; Parker and Preston, 2005), financially constrained individuals are more likely to limit their investing behavior to precautionary saving and to avoid risky and illiquid financial instruments or those correlated with their labor income (Haliassos and Hassapis, 2002; Cocco et al., 2005; Davis et al., 2006). Thus, an investigation of the role of gender in the access to credit is essential to understand the determinants of gender differences in the investment behavior. Although a number of studies investigate gender discrimination in credit markets (Cavalluzzo et al., 2002; Alesina et al., 2009; Muravyev et al., 2009), the evidence is inconclusive and further research is needed. In particular the impact of gender on the access to direct lending needs more exploration.

## 1.2 Contribution of this Work

The literature review in the previous section shows that many questions related to the individual financial behavior remain unresolved. For instance, there is a lack of empirical evidence showing how risk attitudes affect the degree of diversification in financial portfolios. Furthermore, there is still no agreement in the literature regarding the role of gender in financial risk-taking. Finally, the existing evidence is inconclusive with respect to the question of whether females and males have equal access to external finance in credit markets. These gaps in the literature motivate the choice of topics addressed in this thesis. In particular, the thesis provides empirical evidence on the following issues:

(1) Do individual risk attitudes affect the decision makers' propensity to diversify their portfolio of financial assets?

(2) Does gender affect the probability of investing in risky financial assets and the share of wealth allocated to these assets?

(3) Conditional on investing in risky financial assets, do males take bigger risks than females?

(4) Does gender determine the chances to get funds in credit markets?

Accordingly, the thesis comprises four studies whereas each study addresses one of the listed questions.

**Do individual risk attitudes affect the decision makers' propensity to diversify their portfolio of financial assets?**

This question is addressed in the paper "*The Role of Risk Attitudes in Portfolio Diversification Decisions: Evidence from German Household Portfolios*" written jointly with Dorothea Schäfer and Andreas Stephan.

This paper contributes to the literature by examining the effects of self-reported risk aversion on the individuals' propensity to diversify their financial portfolios. The analysis is based on a sample of 2,628 individuals surveyed annually from 2004 to 2007 by the German Socioeconomic Panel (GSOEP).[3] Using these data, we test the hypothesis that individuals' risk attitude affects the probability of holding a specific combination of the following six types of financial assets: 1) saving deposits, 2) mortgage savings plans, 3) life insurance policies, 4) fixed-interest securities issued by the government and banks, 5) equity and security papers of listed companies and 6) equity of non-listed firms.

The capital asset pricing model (CAPM) assumes that investors allocate their wealth across all assets available in financial markets. Yet, the empirical evidence suggests that the portfolio composition varies significantly among investors. Moreover, most of people hold under-diversified portfolios (Campbell, 2006). We hypothesize that risk attitude is one of the factors that contributes to this phenomenon. Specifically, the risk attitude of a decision maker can influence his/her willingness to hold a specific combination of assets, because the composition of a portfolio determines its riskiness. As to the direction of the relationship between risk attitude and the propensity to diversify asset holdings, two different predictions are possible. On the one hand, the propensity to diversify can be positively related to the investors' risk aversion. This relationship should emerge if diversification leads to a reduction of the portfolio riskiness. For instance, when instead of investing all savings in a single risky asset, an investor allocates the wealth among a number of not perfectly correlated assets, this can reduce the risk (Markowitz, 1952). On the other hand, an investor may withhold from acquiring additional assets if this extension increases portfolio risk. Such situation can emerge when a portfolio consists only of risk-free assets, so that

[3]The authors greatly acknowledge the efforts of the DIW colleagues for developing this unique and very rich data base and for their assistance with using the data.

adding a risky asset implies higher risk. In this case, there will be a negative relationship between risk aversion and the propensity to diversify.

Our analysis shows that both types of the relationship take place. Firstly, we find evidence of a negative relationship between the risk aversion and the propensity to diversify. For instance, the probability of holding an incomplete portfolio of risk-free assets increases with risk aversion. Such a portfolio can be diversified only through acquiring risky assets, which implies more risk. Accordingly, the willingness to diversify in this way is negatively related to a person's risk aversion. This relationship is also found when the analysis is performed only on a sub-sample of relatively wealthy people (with wealth exceeding the sample median wealth) or the richest people (with wealth exceeding the 75th percentile of the sample distribution). Hence, risk attitudes affect the propensity to diversify independently of wealth.

Secondly, we find evidence of a positive relationship between the risk aversion and the level of diversification. Specifically, the probability of owning an incomplete portfolio of risky assets decreases with risk aversion. In this case, more diversification can be achieved by acquiring some risk-free assets, which implies a reduction of the portfolio risk. Accordingly, the willingness to diversify is positively related to the risk aversion.

Consistent with previous literature, we find that most of individuals tend to hold under-diversified portfolios consisting of a few safe assets. A possible explanation of this relationship is that individuals are credit constrained and, hence, depend on a "safety buffer" comprising of safe and liquid assets to smooth their consumption. Accordingly, the tendency to confine asset holdings to a "safety buffer" should be positively related to a decision-maker's risk aversion. This conjecture is supported by our finding that the probability of holding a fully diversified portfolio is negatively related to the risk aversion.

An important implication of our findings is that risk attitude should be considered as an important determinant of portfolio diversification that helps explain the high incidence of under-diversified portfolios.

**Does gender affect the probability of investing in risky financial assets and the share of wealth that is allocated to these assets?**

The joint study, with Oleg Badunenko and Dorothea Schäfer, "*Effects of individuals' risk attitude and gender on the financial risk-taking: Evidence from national surveys of household finance*" addresses this question by analyzing the behavior of males and females in four European countries: Austria, Italy, the Netherlands and Spain. Although data on household finance are also available for other countries, representative surveys of peoples' finances that collected specific information needed for the purpose of the study – in particular, the information about the gender and the risk attitude of the decision makers and the composition of the financial portfolios – is available only for these four countries.

Looking at the financial behavior in a cross-country setting is particularly interesting as it allows determining whether differences in the behavior of males and females vary across countries. With respect to gender differences in financial behavior, one country-specific factor is of key importance, namely, the level of gender equality in a given society.[4] This factor can lead to different behavior by males and females in financial markets.

Our main findings can be summarized as follows. While in all four countries females report lower willingness to take risks than males, gender differences in the actual risk-taking are not always present. Specifically, we find that in all four countries females are less likely to acquire risky financial assets. However, conditional on having risky assets, gender has no effect on the fraction of wealth allocated to these assets in all countries, except Italy. According to the 2009 Gender Gap Report, Italy has the greatest gender inequality, when compared to the other three countries. This country also stands out with respect to the relationship between the actual risk taking and the reported risk attitudes. In particular, in Austria, the Netherlands and Spain, we find that the estimated gender differences in the likelihood to own risky assets vanish when we control for reported attitudes towards risks. Hence, males and females seem to behave in accordance with their own assessment of their willingness to take risks. In contrast, in Italy, males and females reporting the same willingness to take risks behave differently: Conditional on the willingness to take risks, females are found to be less likely to own risky financial assets than males. This discrepancy disappears, however, when we look at the fraction of wealth invested in the risky assets. Conditional on risk attitude, Italian investors allocate the same fraction of wealth to risky assets regardless of gender.

These findings have an important implication. Specifically, gender cannot always serve as a good predictor of actual risk taking. First, gender is strongly correlated with the probability of acquiring risky financial assets, but not with the decision regarding the allocation of wealth between the safe and the risky assets. Secondly, the effect of gender on the propensity to take risks depends on the cultural environment. In particular, in countries with greater gender equality, males and females with equal risk attitude behave similarly, while in countries with relatively greater gender inequalities, gender differences in behavior persist even between people with the same risk attitude. Accordingly, we argue that in the societies with relatively high gender equality, individual risk attitudes convey more accurate information about actual risk taking than gender and is, therefore, a much better predictor of the financial risk-taking than gender. In countries with relatively high gender inequality the relationship is converse: the actual risk taking seems to depend more on gender than on the risk attitude.

[4]Evidence on the level of gender equality is provided by the 2009 Global Gender Gap Report of the World Economic Forum, published online at http://www.weforum.org

**Conditional on investing in risky financial assets, do males take bigger risks than females?**

In the previous study we find that females allocate the same fraction of wealth to risky assets as males, conditional on investing in these assets. But does it also mean that males and females take the same amount of risk? Survey data do not facilitate answering this question as no information on the distribution of returns to the owned assets is provided.

The paper "*Does Gender Affect the Risk Propensity of Retail Investors? Evidence from Peer-to-Peer Lending*" attempts to provide evidence on this question by analyzing the data that contain information about individuals' investments and the generated payoffs. Hence, it is possible to quantify the returns to investments and the risk taken by each investor. The data are collected in the largest German marketplace for peer-to-peer lending *Smava.de*. Peer-to-peer lending is the borrowing and lending of money between private individuals without intermediation of a financial institution. The loans are neither collateralized nor guaranteed and lenders can incur losses if borrowers default. Hence, the lenders can be seen as investors who fund risky investment projects, which make the data suitable for an analysis of investment behavior. The data set is comprised of observations on 54,455 investments made by 5,671 investors over three years between March 2007 and March 2010.

The aim of the study is to answer the question: Do females investing in peer-to-peer loans take less risks than male investors? Riskiness of a loan is measured by the variance of the return expected from the loan. Accordingly, a comparison of propensity to take risks between males and females can be done by relying on the mean-variance framework. In particular, I test whether the willingness of a female investor to fund a loan decreases as much as the willingness of a male investor in response to a marginal increase in the standard deviation of return to the loan, holding the expected return constant. Gender effect on the investors' responses is estimated using mixed logit regression – a qualitative choice model that accommodates repeated choice data. Repeated choice arises because during the observation period most investors make several investments.

The results of the estimation show that gender does not matter for investors' appetite for risk. A marginal increase in the standard deviation of expected return equally affects the willingness of males and females to invest. Moreover, no differences between male and female investors are found with respect to other characteristics of projects that may serve as a proxy for projects' riskiness. Hence, the data on peer-to-peer lending do not support the conjecture that women tend to take less risks than their male counterparts when investing. Thus, the present study supports and extends the literature showing that, conditional on investing in risky financial assets, males do not take bigger risks than females.

**Does gender determine the chances to get funds in credit markets?**

Previous studies investigated the treatment of female borrowers in the traditional bank credit markets, however, provided inconclusive evidence (Cavalluzzo et al., 2002; Alesina et al., 2009; Muravyev et al., 2009).

The joint paper, with Dorothea Schäfer, "*Effect of Gender on Access to Credit: Evidence from a German Market for Peer-to-Peer Lending*" analyzes the role of gender in access to credit outside the banking sector. Specifically, we look at the treatment of male and female borrowers in a German market for peer-to-peer lending called *Smava*. Peer-to-peer lending is an innovative an rapidly growing form of credit markets where funds are procured from individuals to individuals. Ravina (2007), Pope and Sydnor (2008) and Duarte and Young (2009) look at the borrowing in a US peer-to-peer lending platform *Prosper* and conclude that females have better chances to obtain credit than males.

Our analysis of the lending on the German platform does not reveal any significant gender differences in the probability of obtaining a loan when all observable characteristics of the loan applications are taken into account. Therefore, we conclude that no gender discrimination takes place on the German platform. This finding, combined with the evidence provided on the peer-to-peer lending in the USA, shows that outside the banking sector female borrowers are not treated more poorly than male borrowers. At the same time, a preferential treatment of female borrowers documented at the US peer-to-peer lending platform indicates that this market place, in contrast to the German market place, is not free of discrimination.

These divergent results, obtained from the United States and Germany, could result from differences in the sampled platforms' procurement mechanisms or from the country-specific factors. However, because each of the studies, including the present one, focus on a single peer-to-peer lending platform, no conclusions regarding the role of these factors can be derived. It is a goal of future research to conduct a comparative analysis of different platforms in order to identify the determinants of the specific treatment of different borrower groups.

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# Chapter 2

# The Role of Risk Attitudes in Portfolio Diversification Decisions: Evidence from German Household Portfolios

*Joint work with Dorothea Schäfer and Andreas Stephan*

***Abstract***: This paper explores the relationship between self-declared risk aversion of private investors and their willingness to hold diversified portfolios of financial assets. The analysis is based on household survey data from the German Socioeconomic Panel (SOEP) that provides a reliable measure of individual attitudes towards financial risk. Our findings suggest that more risk averse households tend to hold incomplete portfolios consisting mainly of a few risk-free assets. We also find that the propensity to diversify is highly dependent on whether liquidity and safety needs are satisfied. We conclude from this evidence that the utility derived by risk averse households from portfolios consisting of only risk-free assets overcompensates the benefits of a better portfolio performance that can be achieved though diversification.

***JEL***: D14, G11
***Keywords***: private households, portfolio diversification, risk aversion

## 2.1 Introduction

According to the capital asset pricing model (CAPM), investors allocate their financial wealth across all assets available in the market and hence hold diversified portfolios. However, numerous empirical studies find that willingness to diversify varies significantly across investors and that a large portion of private investors holds only a small subset of available assets (Hochguertel et al., 1997; King and Leape, 1998; Börsch-Supan and Eymann, 2000; Burton, 2001; Campbell, 2006; Yunker and Melkumian, 2010).

The literature offers a number of explanations for the lack of diversification. Specifically, it is conjectured that incomplete portfolios are attributable to high transaction and search costs (King and Leape, 1987; Merton, 1987), to taxes that treat some assets types preferentially over the other types (King and Leape, 1998), to the lack of information about investment opportunities (King and Leape, 1987), and to the poor financial sophistication of investors (Goetzmann and Kumar, 2008). Empirical tests prove that these factors indeed play an important role in the portfolio composition decisions, however, they do not fully explain the differences in portfolio compositions among individual investors and the high incidence of under-diversified portfolios. For instance, it is hard to reconcile the argument of transaction costs with under-diversification of portfolios of rich people or incomplete information with the behavior of experienced and sophisticated investors.

We think that, in addition to the factors mentioned above, investors' propensity to diversify can be also affected by another factor, namely, the individual risk attitude. Specifically, risk attitude of a decision maker can influence his/her willingness to hold a specific combination of assets, because the composition of a portfolio determines its riskiness. As to the direction of the relationship between the risk attitude and the propensity to diversify asset holdings, two different predictions are possible. On the one hand, the propensity to diversify can be positively related to the investors' risk aversion. This relationship should emerge if diversification leads to a reduction of the portfolio riskiness. For instance, when instead of investing all savings in a single risky asset, an investor allocates the wealth among a number of not perfectly correlated assets, this can reduce the risk (Markowitz, 1952). On the other hand, an investor may withhold from acquiring additional assets if this extension increases the portfolio risk. Such situation can emerge when a portfolio consists only of risk-free assets, so that adding a risky asset implies higher risk. In this case, there will be a negative relationship between risk aversion and the propensity to diversify. Several empirical studies included risk attitude as an explanatory variable in their models of portfolio composition (King and Leape, 1987, 1998; Kelly, 1995). However, they do not discuss the findings regarding its effect on the probability of holding a particular combination of assets.

This study takes a closer look at the relationship between investors' risk attitude and their propensity to diversify financial portfolios and investigates the significance and the direction of this relationship. The analysis is based on the data on the assets holdings of German households collected by the German Socioeconomic Panel (SOEP). Specifically, we relate individuals' attitude towards financial risks to their propensity to diversify among six broad classes of financial assets: saving deposits, mortgage savings plans, fixed-interest securities, shares of listed companies and equity of non-listed firms.

The extent of portfolio diversification is measured in two ways. The first measure is the number of distinct asset types held in a portfolio. Despite its simplicity, this measure reflects decisions of individuals who follow a "naive" diversification strategy according to the principle "don't put all your eggs in one basket". Such strategy is often observed in the behavior of nonprofessional investors who split their wealth evenly among all available assets types hoping that this will reduce the risk of the entire portfolio (Benartzi and Thaler, 2001). The second measure of diversification is designed to capture more sophisticated investment strategies. Particularly, a sophisticated investor differentiates the assets according to their return and risk properties and thereby assigns them to different "return-risk" classes. Based on this classification, the investor then decides what combination of assets to hold given some expectations regarding the portfolio returns and riskiness.

Information about risk attitude that we use is collected within the SOEP-survey by asking the respondents how willing they are to take financial risks. Dohmen et al. (2005) show that the SOEP survey measure of risk attitude is behaviorally relevant, in the sense that it is predictive of actual risk-taking behavior.[1] Aside from this valuable information, the SOEP data give us several other advantages. Firstly, information about the ownership of different asset types allow us to investigate real-life portfolio decisions and hence to provide more reliable evidence than it would be possible in an experimental setting.[2] Secondly, the data set includes indicators of who is the main decision maker in a household and provides detailed socioeconomic information on this individual as well as the whole household. Thirdly, the survey is conducted yearly and allows tracing individuals and households over time. Finally, a significant advantage of the data is the size of the sample. Even after we drop all observations with missing data and exclude cases where a decision maker could not be identified, we still have a sample of 2,628 individuals observed during four years – from 2004 to 2007 – which amounts to a total of 10,512 observations.

The results of our analysis show that risk aversion has a significant effect on the propensity to diversify. Moreover, we find that both the negative and the positive relationship between the risk aversion and the willingness to diversify take place. The negative relationship between the risk aversion and the propensity to diversify is found in the following instances. Firstly, the negative relationship emerges when the naive diversification strategy is considered, that is when the extend of diversification is measured by the number of different assets types held in a portfolio. In this case, the degree of diversification decreases with the risk aversion.

Secondly, the negative relationship between the propensity to diversify and the risk aversion is found when the sophisticated diversification strategy is considered. In particular, the

[1] Other studies also demonstrate that self-declared risk attitudes are good predictors of the actual investment behavior (Kapteyn and Teppa, 2002; Fellner and Maciejovsky, 2007).

[2] Vlaev et al. (2008) present evidence that people behave more risk averse when investing in real life than when making investment choices in laboratory experiments.

probability of holding an incomplete portfolio increases with risk aversion if the portfolio consists only of risk-free assets. Such portfolio could be only diversified by acquiring risky assets which implies more risk. Accordingly, the willingness to diversify in this way is negatively related to a person's risk aversion. Furthermore, the probability of holding a fully diversified portfolio comprising all asset types available at the market is also negatively related to the risk aversion. In this case, a less diversified portfolio may be preferred to a more diversified portfolio when the earlier comprises a smaller number of risky assets or no risky assets at all. This relationship is also found when the analysis is performed only on a sub-sample of relatively wealthy people (with wealth exceeding the sample median wealth) or the richest people (with wealth exceeding the 75th percentile of the sample distribution). Hence, risk attitude affects the propensity to diversify independently of wealth.

The positive relationship relationship between the risk attitude and the level of diversification is found only in one instance. Specifically, when considering the sophisticated diversification strategy, we find that the probability of owning an incomplete portfolio decreases with risk aversion if the portfolio consists of only risky assets. In this case, more diversification could be achieved by acquiring some risk-free assets, which would lead to a reduction of the portfolio risk. Accordingly, the willingness to diversify is positively related to risk aversion.

We also find that the majority of under-diversified portfolios consist only of safe assets. This observation sheds some light on the reasons of the negative relationship between risk aversion and diversification decisions. As argued by Keynes (1936), economic activity of private households is dominated by safety and liquidity needs. From the point of view of an average household that is credit constrained, financial wealth plays a role of a "safety buffer" needed to smooth consumption during periods of low income. Since asset holdings are meant to provide safety in the first place, adding any risky assets to a portfolio can be viewed as adding more risk and reducing the "safety buffer". Thus, the tendency to confine asset holdings to a "safety buffer" should be positively related to a decision-maker's risk aversion. Our results are in line with this conjecture. We find that the more risk averse an investor is the more he is inclined to hold an incomplete portfolio consisting of a few safe assets. Furthermore, when regressing the number of risky assets held in a portfolio on the holdings of safe assets, we find a positive effect of the number of safe assets on the number of risky assets. Hence, a decision-maker is more likely to add some risky assets to his portfolio when safety needs are satisfied.

Thus, due to the important role of precautionary motives in the portfolio decisions of private households and to the positive relationship between risk aversion and accumulation of safe assets, risk aversion has a negative impact on the propensity to hold diversified portfolios. For this reason, individual risk attitude should be considered as an important determinant of diversification decisions that helps explain the differences in the portfolio composition among households and the high incidence of under-diversified portfolios.

The remainder of the paper is organized as follows. In the next section, we review the existing literature about the role of risk aversion for portfolio diversification. The third section describes our data and provides more details on the measures of portfolio diversification. The fourth section presents the indicator of individual risk aversion. In the fifth section, we test the main hypothesis and discuss the results. In section six, we analyze the role of precautionary motives for the diversification. The last section concludes.

## 2.2 Literature Review

Academic research into determinants of portfolio diversification can be traced back to the mean-variance analysis of Markowitz (1952). Markowitz develops a model that explains how investors select assets if they only care about the mean and variance of portfolio returns. One of the model's implications is that investors with high risk aversion prefer diversified portfolios with moderate expected returns to undiversified portfolios with high expected returns because diversification allows reducing portfolio risk associated with variance of returns on individual assets. However, the capital assets pricing model (CAPM) that derives from Markovitz's mean-variance analysis, does not predict any relationship between the risk aversion and the level of diversification. In contrast, the model assumes that regardless of the degree of risk aversion investors hold diversified portfolios, i.e. invest in all assets available in the market. Risk aversion determines only the amount of wealth allocated to individual assets.

Despite the predictions of CAPM numerous empirical studies show that investors – and especially private households – often hold incomplete portfolios (Hochguertel et al., 1997; King and Leape, 1998; Börsch-Supan and Eymann, 2000; Burton, 2001; Campbell, 2006; Yunker and Melkumian, 2010). Starting with Blume and Friend (1975), empirical studies try to explain why many private investors abstain from investing in risky financial assets and usually hold under-diversified portfolios consisting of few risk free assets (Blume and Friend, 1975; Kelly, 1995; King and Leape, 1998; Benartzi and Thaler, 2001; Campbell et al., 2003; Gomes and Michaelides, 2005; Polkovnichenko, 2005; Goetzmann and Kumar, 2008). However, only few of them analyze how risk aversion affects the level of diversification.

A theoretical study by Campbell et al. (2003) shows that the level of diversification might be a hump-shaped function of risk aversion. Specifically, individuals with intermediate levels of risk aversion are predicted to hold multiple assets including risky investments; in contrast, extremely risk-averse and risk-loving investors should hold less diversified portfolios. The researchers explain this idea by noting that some risky assets can be used to hedge against the fluctuations in their own future returns. This hedging feature should be attractive for investors with intermediate levels of risk aversion, forming the middle of the demand “hump”. On the outer sides of this hump are the very conservative investors, who tend to avoid any risk, and the extremely risk-tolerant investors, who have little interest in the intertemporal hedging. Therefore, very risk averse investors should choose to hold undiversified portfolios consisting mainly of safe assets; extremely risk-loving investors should hold undiversified portfolios too, however in their case, these portfolios will comprise few risky assets; finally, investors with moderate risk aversion are expected to hold the most diversified portfolios consisting of all available assets.

Gomes and Michaelides (2005) formulate a model of intertemporal portfolio choice explaining the probability of diversification between two asset types: a risk free asset and a risky one. The results of the analysis imply that probability of owning both types of assets is an increasing function of risk aversion. The explanation of this relationship is risk-averse investors are more prudent in money management and, respectively, are more likely to accumulate wealth than their risk-loving counterparts. Availability of considerable financial resources in turn motivates investors to acquire additional assets. Risk-prone investors, in contrast, accumulate very little wealth and, correspondingly, most of them do not have enough means to cover the fixed costs of market participation and hence hold only few assets.

Empirical studies provide only scarce evidence on the effects of risk attitudes on diversification decisions. Kelly (1995) uses data from the 1983 Survey of Consumer Finances to assess the level of diversification of the financial portfolios of US households. Diversification is measured in terms of the number of distinct stocks held in a portfolio. While controlling for a large number of investors’ characteristics, the authors find a negative effect of risk aversion on the number of stocks held in the portfolios of wealthy people. Also King and Leape (1987, 1998) find evidence of a negative relationship between risk aversion and diversification. Yet, none of these studies discusses why does risk attitude matter for diversification and why is the relationship negative.

In sum, existing theoretical models of portfolio decisions provide conflicting predictions regarding the relationship of risk aversion and diversification. Furthermore, empirical evidence on the issue is very scarce. This paper contributes to the literature by examining the effects of risk aversion using micro-level data from the SOEP survey.

## 2.3 Evidence on household portfolios from the SOEP

### 2.3.1 The data set

Our analysis is based on a sample of 2,628 individuals that participated in four subsequent waves, 2004 through 2007, of the the German Socioeconomic Panel (SOEP) survey. The data set presents a balanced panel. The unit of observation is an individual, single or a member of a multi-person household. Most of the socioeconomic data including the risk attitudes are collected at the individual level. Nevertheless, there is also detailed information about the households that the surveyed individuals belong to.

An important issue that should be addressed in a study of investment behavior is the question about who makes investment decisions in multi-person households. In order to identify the decision maker we use two indicator-variables provided by the SOEP. The first variable indicates who is the household head in a household. The SOEP defines the household head as a person with the best knowledge about conditions under which the household functions. Using this information, we keep only the household heads in our sample. The second variable provides information about money management within multi-person households. The exact wording of the respective survey question is: "How do you and your partner (or spouse) decide what to do with the income that either you or your partner or both of you receive?: (1) Everyone looks after his own money, (2) I look after the money and provide my partner with a share of it, (3) My partner looks after the money and provides me with a share of it, (4) We put the money together and both of us take what we need, (5) We put a share of the money in together, and both of us keep a share of it for ourselves". Only individuals who chose alternatives 1 and 2 are kept in our sample. Thus, the sample consists of individuals who are household heads and are primarily responsible for the management of the household money.

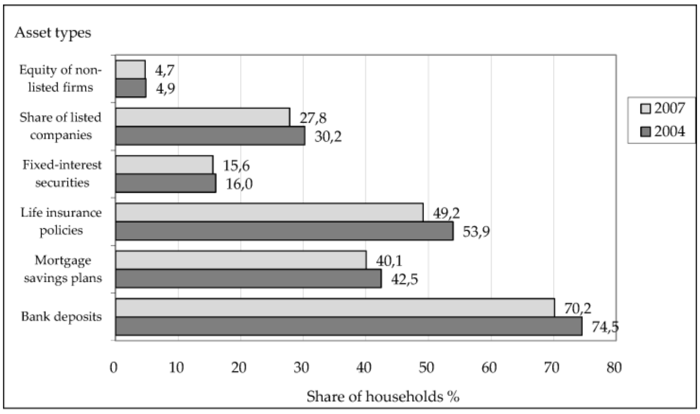
### 2.3.2 Ownership of financial assets

The SOEP survey contains information on whether a household owns any of the following six types of financial assets: bank saving deposits, mortgage savings plans[3], life insurance policies, fixed-interest securities (including federal savings bonds, saving bonds issued by banks and mortgage-backed bonds), security papers of listed companies (including stocks, bonds and equity warrants held directly or through mutual funds), and equity of non-listed firms. Information about the money amounts invested in each asset class is not provided.

Figure 2.1 documents the fraction of households owning the specified asset types at the beginning and at the end of the observation period. Apparently, bank deposits, life insurances and mortgage savings plans are the three financial assets that are most frequently held by private households in our sample. The figures do not change very much over the four years, although a slight decline in the ownership of bank deposits and life insurances is observable.

[3]The German term is “Bausparvertrag".

Figure 2.1: Ownership rates of different asset types in the sample




### 2.3.3 Measures of diversification

Despite the fact that the analysis of portfolio diversification has a long history, there is no common approach to the measurement of diversification in household portfolios. Empirical studies suggest diverse approaches depending on the data at hand. Blume and Friend (1975) use the total number of securities constituting a portfolio as a measure of diversification. Goetzmann et al. (2005) correct the total number of financial instruments for the correlation among returns on these instruments in order to account for passive diversification.[4] These measures are well suited for an analysis in the framework of Markowitz's mean-variance approach. However, both methods require the information about share of wealth allocated to each individual security paper. This information of all is rarely provided in household surveys.

Most household surveys report which assets are held or at most what amounts are invested in broad groups of assets. Beside the difficulty to obtain exact information about pecuniary circumstances from private persons, the tendency to collect unspecific information stems from the fact that most households hold very simple portfolios. For example, Campbell (2006) shows that the majority of household financial portfolios in the United States are poorly diversified. Liquid assets (e.g., cash, demand funds) play the dominant role for the poor, while less liquid savings (e.g., savings accounts, life insurance contracts) dominate the portfolios of middle-class households. Carroll (1995) documents a similar pattern of portfolio composition among European households. Moreover, as shown by Benartzi and Thaler (2001), it is not rare for nonprofessional investors to follow some naive or heuristic diversification strategy, e.g., *1/n strategy*, according to which investors split their wealth evenly among *n* available assets.

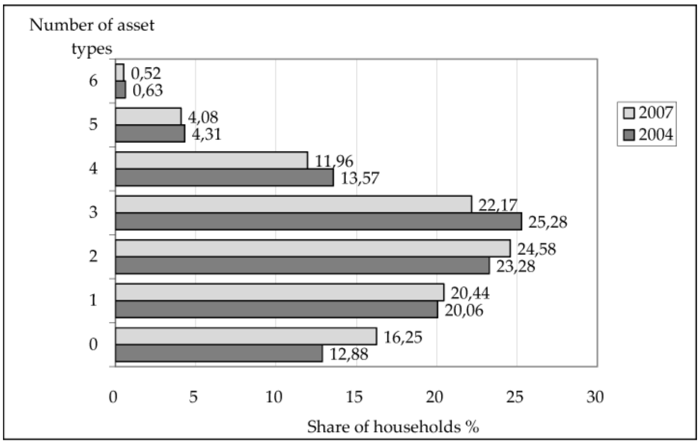
[4]Passive diversification means that correlation between individual assets included in a portfolio is not taken into account, only the number of assets matters.

Taking into account the specifics of our data and the tendency of households to hold simple portfolios, we construct two alternative measures of portfolio diversification – "naive diversification" and "sophisticated diversification".

### Naive diversification

Naive diversification is achieved by investing in all available assets.[5] Accordingly, the more asset types are held in a portfolio, the more diversified the portfolio is. The SOEP data allow identification of six distinct asset types. Figure 2.2 shows the distribution of individuals in our sample by the number of asset types held. Apparently, the largest fraction of individuals allocates wealth among two or three asset types; while owners of six-assets portfolios make up less than one percent of the sample.

Figure 2.2: Number of asset types held in portfolios




### Sophisticated diversification

Our second measure of diversification is constructed to capture more sophisticated investment patterns. It accounts not only for the number of assets, but also for their degree of risk and combination in a portfolio. The measure is constructed as follows.

The six available asset types are grouped into three classes according to their riskiness: *low risk*, *moderate risk*, and *high risk* (see Table 2.1). Because we do not know the returns on each individual asset, defining riskiness according to the mean-variance approach is not possible. Instead, we use a more simple, but feasible, categorization drawing upon Blume and Friend (1975) and Börsch-Supan and Eymann (2000).[6]

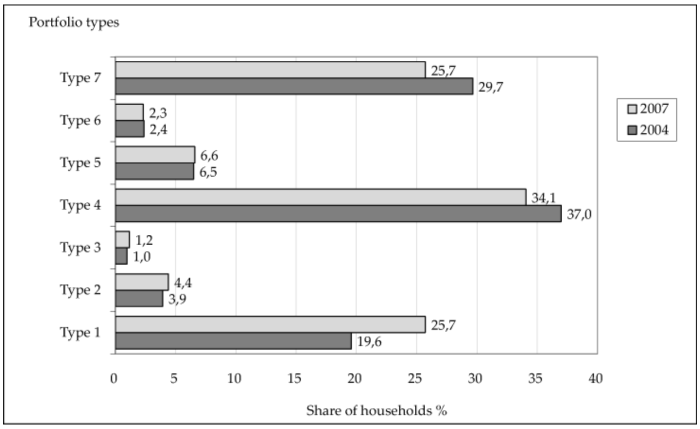
[5]The term "naive diversification" is often used to reflect the fact that an equal amount of wealth is attached to all assets available DeMiguel et al. (2009). We refer only to the number of asset types due to the data constraints of the SOEP.

[6]This approach has also been applied by Alessie et al. (2000), Banks and Smith (2000), Bertaut and Starr-McCluer (2002), Guiso and Jappelli (2000).

This categorization is justified as follows. Bank deposits are clearly safe because their returns do not exhibit any variation and are guaranteed by the financial institution. The returns on fixed-interest assets are also stable; however, the real payoff depends on the duration and on the issuer's rating. Holders of life insurance policies do not bear the risk of losing the entire investment, but the real return upon termination is uncertain and can be significantly lower than the expected return. Listed securities and equity of non-listed firms are the most risky, since stock prices and dividends as well as firms' value are volatile and uncertain. In accordance with the "no free lunch principle" the lowest expected return is assigned to assets in the *safe class*; *relatively risky assets* are assumed to have moderate expected returns; the highest expected return is assigned to assets in the *risky class*. We assume that the defined asset classes are not perfectly positively correlated.

Based on this classification rule, we define seven portfolio types (Table 2.2). A portfolio that consists of assets from only one class, i.e., either safe, relatively risky, or risky, has the least degree of diversification and is referred to as *undiversified*. Depending on what asset type is held, an undiversified portfolio can have low risk (Type 1), moderate risk (Type 2), or high risk (Type 3). A portfolio that includes assets from at least two different classes is referred to as *quite diversified*. Different types of quite diversified portfolios are defined according to the degree of risk of the included individual asset types: Type 4 includes safe and relatively risky assets, Type 5 consists of safe and risky assets, and Type 6 contains relatively risky and risky assets. Finally, the *fully diversified* portfolio (Type 7) is one that includes assets from all three classes.

Figure 2.3: Distribution of individuals by portfolio types




Type 1: undiversified portfolio of safe assets;
Type 2: undiversified portfolio of relatively risky assets;
Type 3: undiversified portfolio of risky assets;
Type 4: quite diversified portfolio comprising safe and relatively risky assets;
Type 5: quite diversified portfolio comprising safe and risky assets;
Type 6: quite diversified portfolio comprising relatively risky and risky assets;
Type 7: fully diversified portfolio includes assets from all three risk groups.

The sample distribution with respect to the seven portfolio types (Figure 2.3) indicates that households have a strong tendency towards safety: most of them hold either incomplete portfolios of safe assets or a mix of safe and relatively risky assets. Individuals who diversify their investments over all three asset classes are also numerous. Owners of portfolios with few risky assets constitute a minority in our sample. Hence, if the risk/return profiles assigned to the six asset types are correct, we can argue that most households choose to forgo higher returns in favor of safety of their investments.

## 2.4 Risk aversion

As a measure of risk aversion, we use individuals' self-reported attitudes towards financial risks. This information is collected by the SOEP in 2004 by asking the respondents to assess the strength of their willingness to take risks when investing in money. The exact wording of the SOEP question is: "How would you rate your willingness to take risks in financial matters on a scale from 0 (not willing to take any risks) to 10 (fully prepared to take risks)?" The validity of the individuals' responses to the question was verified experimentally and it was shown that the self-reported attitude towards financial risk is consistent with actually done investment choices.[7]

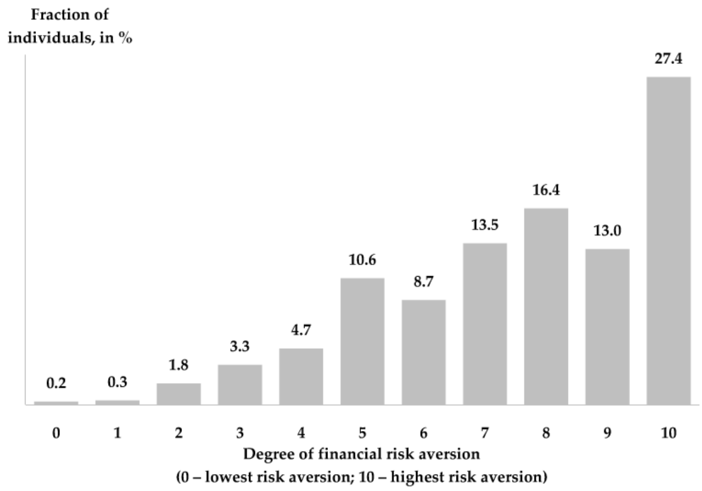
Two adjustments are made to the original indicator of risk attitudes to make it suitable for the purposes of our analysis. First, we convert the indicator from being a measure of risk tolerance into a measure of risk aversion. This is accomplished by reversing the scale so that its higher numbers correspond to higher risk aversion: "0" denotes "fully prepared to take risks", i.e. the lowest risk aversion, and "10" denotes "not willing to take any risks", i.e. the highest risk aversion. The new discrete variable that emerges is called *FRA*. Figure 2.4 presents the sample distribution of individuals according to the level of risk aversion in 2004. Apparently, the majority of respondents perceive themselves as highly risk averse.

Because information about risk attitudes is available only in one year, a further adjustment is necessary to make it applicable in a panel-data context. We treat the measure as a time-invariant variable assuming that attitudes towards risks remain stable over the four-year period, which appears to be a reasonable assumption for periods of normal economic conditions.[8]

[7] For details and discussion of the validity tests, see Dohmen et al. (2005).

[8] Barsky et al. (1997) provide evidence that risk preferences are in fact relatively stable over time.

Figure 2.4: Distribution of individuals by degree of risk aversion




## 2.5 Regression analysis

### 2.5.1 The model

The goal of the study is to answer the question how does risk attitude affect the extent of diversification of financial portfolios. To answer this question, we model the probability of observing a certain combination of assets as a function of risk aversion and a set of socioeconomic variables. The later comprise various factors from household- and individual-specific level that are considered as important determinants of investment behavior.[9] Description of the variables is provided in Table 2.4. Summary statistics are reported in Table 2.5.

The two diversification measures are categorical variables with $J$ mutually exclusive and exhaustive alternatives. Specifically, the measure of naive diversification takes on 5 successive values, from 0 to 4, according to the number of asset types owned by a household; the measure of sophisticated diversification takes on 8 values corresponding to the portfolio types defined earlier in Section 3.2.2 including the case when none of the specified asset types are held.

To test the effects of risk aversion on naive diversification we should fit the data to an ordered logistic regression model because of the ordinal nature of the dependent variable. However, after we estimated the model, the results of Brant (1990) test indicated that the parallel regression assumption (also called the proportional odds assumption) is violated

[9]There is a wide agreement in the empirical literature that socioeconomic and demographic characteristics of investors have significant influence on portfolio decisions. In particular, Uhler and Cragg (1971) and Tin (1998) find that differences in income, age, and education explain a large portion of variation in number of different financial assets held by U.S. households; evidence from more recent studies supports this finding (King and Leape, 1998; Hochguertel et al., 1997; Börsch-Supan and Eymann, 2000; Burton, 2001; Campbell, 2006).

and the data should be fitted to another model. Similar to Uhler and Cragg (1971), we employ a pooled multinomial logistic regression that relaxes the proportional odds assumption. Furthermore, the Hausman test for independence of irrelevant alternatives (IIA) confirmed that multinomial logit model is more appropriate in our case.

The model is specified as follows. For the case of $J$ outcomes, where J=5, the probability of observing a particular outcome, $P(Y_j)$, is:

$$P(Y_j) = \frac{exp(X'\beta_j)}{\sum_{n=1}^{J} exp(X'\beta_n)}, \tag{2.1}$$

$$n = 0,1,2,...,J; \quad j = 0,1,2,...,J; \quad j \neq n.$$

$X$ is the vector of explanatory variables that includes the measure of financial risk aversion and a range of control variables. Year dummies are also included in order to control for time-specific effects. We compute robust standard errors using Huber-White "sandwich" estimator of variance that allows for clustering of observations by individuals.

The effects of risk aversion on sophisticated diversification are estimated using the same multinomial logistic regression model with the sole difference that the number of outcomes, $J$, is now equal to 8. Control variables are the same as in the case with naive diversification.

### 2.5.2 Impact of risk aversion on "naive" diversification

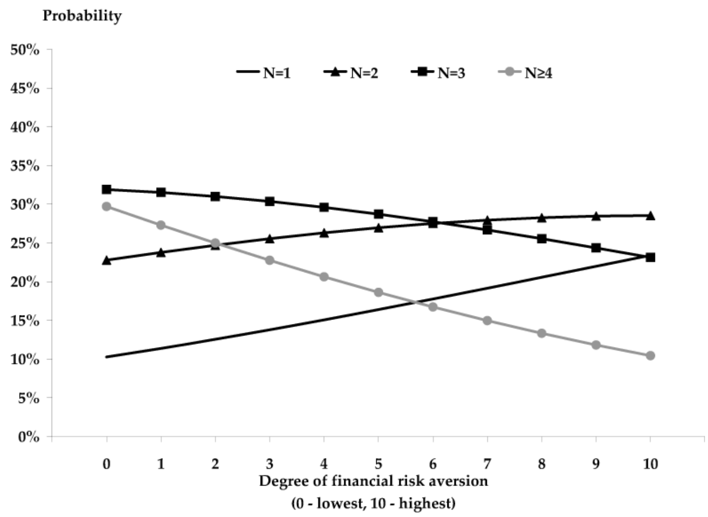
The estimated marginal effects of explanatory variables on naive diversification and the predicted probabilities of holding a given number of assets are documented in Table 2.5. The marginal effects and probabilities are calculated at FRA=5, while continuous variables are held at their sample means and dummy- and count-variables are held at zero.

Overall, the predicted probabilities are largely in line with the sample distribution of individuals with respect to the number of asset types held in a portfolio. Individuals with risk aversion score equal to 5 are most likely to hold portfolios of two and three assets. The respective predicted probabilities are 29 and 27 percent.

The estimated marginal effects suggest that risk aversion is an important determinant of the number of assets held in a portfolio. The probability of holding one asset is predicted to increase by one percent when level of risk aversion rises by one unit. The likelihood of a two-asset portfolio is also predicted to rise with increasing risk aversion; the effect is however statistically not significant. The probability of holding more than two assets is negatively related to risk aversion. In particular, an individual is by 0.8 percent less likely to invest in three different assets while likelihood of investing in four and more assets decreases by one percent when risk aversion rises by one.

Because the effects of variables in a multinomial model may vary across the range of the variables' values, it is useful to look at the probabilities of outcomes predicted at all levels of risk aversion. Hence, to provide a more complete picture of the changing effects of risk attitude on diversification, we estimate the probabilities to hold a particular number of asset types for each degree of risk aversion (see Figure 2.5). We find however, that the effects seem to be constant at the whole range of values. Moreover, the figures clearly show a negative relationship between risk aversion and the likelihood of holding multiple assets. The most risk tolerant individuals invest in at least four assets with probability of 20 percent. Their very risk averse counterparts do the same with much lower probability of 10 percent. The likelihood of a three-asset portfolio also decreases with rising levels of risk aversion. On contrast, the line describing the relationship between risk aversion and the probability of holding one asset rises with risk aversion.

Figure 2.5: Effect of financial risk aversion on the probability of holding particular number of asset types in portfolio



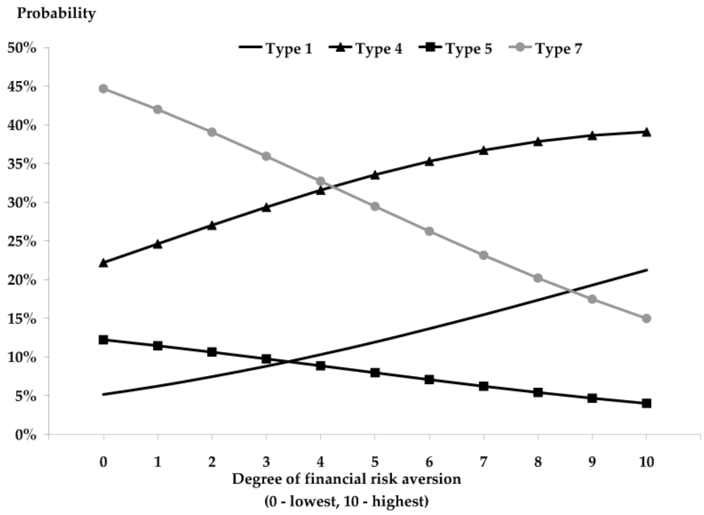

Hence, our results reveal a negative link between risk aversion and diversification. However, robustness of the results should be additionally tested because investors may follow more sophisticated diversification strategies rather than simply going for the number of distinct assets. This issue will be investigated in more detail in the next section.

### 2.5.3 Impact of risk aversion on "sophisticated" diversification

In this section we analyze the effects of individual risk aversion on portfolio diversification assuming that households follow a more sophisticated investment strategy. To this end, we proceed with estimating a model where the measure of sophisticated diversification serves as dependent variable. The estimated marginal effects of risk aversion on the probability of given portfolio types are reported in Table 2.6.

Households with average risk aversion score of 5 are most likely to hold portfolio "Type 4", i.e. quite diversified portfolio comprising safe and relatively risky assets; the estimated probability is 32 percent. Respective marginal effect of the variable FRA suggests that likelihood of this portfolio type rises by one percent if the level of risk aversion increases by one unit. The estimated probability of a fully diversified portfolio is somewhat lower, 24 percent, and is decreasing in risk aversion.

Figure 2.6: Effect of financial risk aversion on the probability of holding a particular portfolio type according to the “sophisticated” diversification rule




Type 1: undiversified portfolio of safe assets;
Type 2: undiversified portfolio of relatively risky assets;
Type 3: undiversified portfolio of risky assets;
Type 4: quite diversified portfolio comprising safe and relatively risky assets;
Type 5: quite diversified portfolio comprising safe and risky assets;
Type 6: quite diversified portfolio comprising relatively risky and risky assets;
Type 7: fully diversified portfolio includes assets from all three risk groups.

Figure 2.6 illustrates how the probabilities of holding the specified portfolio types change with levels of financial risk aversion. The likelihood of undiversified portfolio "Type 1" rises at an increasing rate as risk aversion gets stronger. The relationship between the probability of quite diversified portfolio "Type 4" and risk aversion is also positive. However, the effect is especially strong for the lower than average levels of risk aversion and gets sufficiently weaker for the above average levels of risk aversion. For both portfolio types, the effect is quite plausible. As risk aversion gets stronger, individuals tend to invest in safe assets.

An opposite relationship emerges when we look at the probability of a quite diversified portfolio "Type 5"; the probability decreases almost linearly when risk aversion gets stronger. Since the portfolio "Type 5" is a mix of safe and risky assets, it is not surprising that more risk averse investors are less willing to hold this mix than their more risk tolerant counterparts.

Finally, the effect of risk aversion on the probability of holding fully diversified portfolio "Type 7" is negatively related to risk aversion.[10] Assuming that returns on different asset types are not perfectly positively correlated and there are no transaction or entry costs, we would expect that fully diversified portfolio is more attractive to individuals with moderate risk aversion than to very risk averse or risk tolerant investors. Instead we find a strong and almost linear negative relationship. Thus, our findings disagree with predictions of Campbell et al. (2003) and Gomes and Michaelides (2005) but are in line with findings of Kelly (1995) and King and Leape (1987, 1998).

## 2.6 Extension 1: Wealthy investors

When it comes to portfolio decisions, the amount of wealth plays a crucial role. So far, we attempted to control for the effect of wealth by including wealth as an explanatory variable in the regressions. The estimation results show that wealth has a strong (in economic and statistical sense) effect on the diversification decisions. We also find that when wealth is fixed, risk attitude has a significant effect on the propensity to diversify. From these results, we concluded that risk attitude plays a significant role independently of wealth. However, risk attitude and wealth are correlated. For instance, we find that risk aversion decreases as wealth increases.[11] So, by simply including both variables in a regression model might be insufficient to disentangle their effects. Thus, it is possible that our main result regarding the negative relationship between the diversification and risk aversion emerges due to the collinearity between the risk attitude and wealth.

To prove whether risk attitude is indeed a relevant factor of the diversification decisions regardless of wealth, we perform the analysis presented in the preceding sections on a sub-sample of wealthy people. Specifically, we construct two groups of wealthy individuals: 1) the relatively wealthy people with wealth exceeding the sample median and 2) the rich people with wealth exceeding the 75th percentile of the sample distribution. We then estimate the same regression models as reported in Tables 2.5 through 2.7 separately for each of these sub-samples. The specification of explanatory variables is similar to regressions reported Tables 2.5 through 2.7. One exception is that instead of including dummy variables for the percentiles of the wealth distribution, we now include a continuous variable

[10]We also estimate the effects of risk aversion on the sophisticated diversification in a model where we additionally include ownership of commercial real estate and value of household total assets and liabilities as control variables. As the data on these variables are available for 2007 only, the model is estimated with a cross-sectional data set. Nevertheless, the results obtained for this specification once again confirm the negative relationship between risk aversion and probability of holding a diversified portfolio.

[11]The coefficient of correlation between the risk aversion and the household wealth and is -0.12 (the coefficient is statistically significant at 5% level) and between income is -0.23 (the correlation is statistically not significant). When we regress risk attitude on wealth and control for other socioeconomic characteristics of individuals, we find a statistically significant negative effect of wealth on risk aversion. For brevity, we do not present the results here but we would be happy to provide them to the interested reader upon request.

ln(Wealth) which is a natural logarithm of the household wealth. The results with respect to the effect of risk attitude on the probability of holding a particular combination of assets are reported in Tables 2.8 through 2.10.

The results reveal a similar pattern as the one received for the whole sample of individuals. For instance, for the relatively wealthy and the rich, we find again a negative and statistically significant effect of risk aversion on the probability of holding a fully diversified portfolio. We also find a positive and a statistically significant effect of risk aversion on the probability of holding an incomplete portfolio consisting of safe assets. Finally, the probability of holding an incomplete portfolio of risky assets is negatively related to risk aversion. Hence, our results regarding the effects of the risk attitude hold also for the wealthy people. Therefore we can conclude that risk attitude affects the portfolio diversification decision independently of how wealthy an investor is.

## 2.7 Extension 2: The role of precautionary motives

Our analysis reveals a negative relationship between the manifested individual risk aversion and the probability of holding a diversified portfolio and a positive relationship between the risk aversion and the probability of holding an under-diversified portfolio comprising fisk-free assets. How can this finding be explained? An explanation can be found when one thinks about the motives behind saving by private households. Satisfaction of precautionary needs has long been considered as one of the main motives of personal saving. Already Keynes (1936) suggests that economic activity of private households is dominated by safety and liquidity needs. A number of more recent applied works confirm the relevance of the precautionary motive for saving (Skinner, 1988; Zeldes, 1989; Caballero, 1991; Wilson, 2003; Ventura and Eisenhauer, 2005).

For any particular household, its individual safety needs should determine what mix of assets is held. If this conjecture holds, then the most natural decision for a household would be first and foremost to invest in safe assets like cash and saving deposits. Only when basic precautionary needs are satisfied, a household acquires other, more speculative types of assets, like bonds or stocks. Thus, it is reasonable to assume that if a household owns only one asset type, it will be a safe one. This assumption coincides with what we observe in our sample (see Figure 2.3). Therefore, we expect that individuals' propensity to invest in risky assets is higher when their safety needs are satisfied.

To test this hypothesis, we estimate an additional multinomial logit model. The dependent variable in this model represents the number of risky assets held in a portfolio. The explanatory variables include risk aversion, socioeconomic and wealth variables. In addition, we control for the number of safe assets held in a portfolio, $N_{Safe\,assets}$. Estimated marginal effects are reported in Table 2.7.

As expected, the results confirm a positive relationship between the number of safe assets and the ownership of risky financial assets. Ceteris paribus, ownership of a unit increment in the number of safe assets reduces the probability that a household refrains from risky assets by 9 percent, while the likelihood of owning one risky asset increases by 8.8 percent. The probability of holding two and more risky assets is also positively associated with a unit increment in safe assets. Thus, we can conclude that propensity to diversify by including risky assets into a portfolio is in fact highly dependent on whether safety needs are satisfied.

## 2.8 Conclusions

This paper explores the link between self-declared risk aversion and the level of diversification in financial portfolios of private households. Taking into account a wide range of socioeconomic and demographic characteristics of households, we find that diversification is negatively related to the level of risk aversion. This result is in odds with the mean-variance principle of Markowitz (1952) and the capital asset pricing model. On the other hand, our findings are largely in agreement with Kelly (1995) and King and Leape (1998) who also find a negative influence of risk aversion on the number of assets held in a portfolio.

Our explanation of the finding is that most consumers are credit constrained and hence depend on safe and liquid assets as a "safety buffer" meant to smooth their consumption in periods of low income. Hence, for most individuals the primary function of financial wealth is to serve precautionary and liquidity needs. Respectively, adding any risky asset to portfolio is viewed as adding more risk into portfolio and reducing the safety buffer. The higher the risk aversion the larger safety buffer a household would aim at and the less likely it will be to own risky assets. In effect, more risk averse people are more likely to hold incomplete portfolios consisting of safe and liquid assets.

Obviously, variation in risk attitudes in the population itself does not suffice to explain the high incidence of incomplete portfolios. Other factors like poor financial sophistication, participation costs and other factors discussed in literature play definitely an important role. Therefore, the role of risk attitudes should be considered complementary to the other factors affecting the portfolio diversification.

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# Appendix A

Table 2.1: Categorization of asset types according to their riskiness

| **Low Risk** | **Moderate Risk** | **High Risk** |
|---|---|---|
| Bank deposits | Life insurance policies | Listed securities |
| Mortgage savings plans | Fixed-interest securities | Equity of non-listed firms |

Table 2.2: Definition of portfolio types according to strategies of "sophisticated diversification"

| Portfolio type | Level of diversification | Asset classes included in portfolio | | |
|---|---|---|---|---|
| | | safe | relatively risky | risky |
| Type 1 | Undiversified | + | - | - |
| Type 2 | Undiversified | - | + | - |
| Type 3 | Undiversified | - | - | + |
| Type 4 | Quite diversified | + | + | - |
| Type 5 | Quite diversified | + | - | + |
| Type 6 | Quite diversified | - | + | + |
| Type 7 | Fully diversified | + | + | + |

" + " indicates that at least one asset of particular type is owned, "-" indicates that no assets of particular type are owned.

Table 2.3: Description of explanatory variables

| Variable | Description |
|---|---|
| FRA | Degree of financial risk aversion, on a scale from 0 (very low) to 10 (very high) |
| Household Income | Net annual income of all household members, in Euro |
| Household Wealth | Total value of financial assets and real property owned by the household, in Euro[1] |
| Personal Wealth | The value of personal share of the household's total assets owned by the household head, in Euro[1] |
| Real Property (d) | = 1 if the household owns real property, 0 otherwise |
| Female (d) | = 1 if the household head is female, 0 if male |
| Age | Age of the household head in years |
| University (d) | = 1 if with university degree, 0 otherwise |
| Employed (d) | = 1 if the household head is employed, 0 otherwise |
| Self-Employed (d) | = 1 if the household head is self-employed, 0 otherwise |
| Retired (d) | = 1 if the household head is retired, 0 otherwise |
| Adults | Number of adult household members (older than 18 years) |
| Children | Number of children up to 18 |
| Concerned | A categorical variable indicating whether the individual is concerned about his financial standing (=1 very concerned, 2 = somewhat concerned, 3 = not concerned at all) |
| East Germany (d) | = 1 if the household head lives in East Germany |

*Note*: (d) denotes dummy-variables. [1] Data about financial and real assets were collected by the SOEP in 2002 and 2007 only. For years 2004 through 2006, we calculate total wealth based on the assumption that its value changes linearly over time.

Table 2.4: Summary statistics of explanatory variables

| | 2004 | | 2007 | |
|---|---|---|---|---|
| **Variable** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| FRA | 7.53 | 2.28 | 7.53 | 2.28 |
| Household Income | 25,657 | 16,014 | 27,343 | 20,841 |
| Household Wealth | 12,883 | 44,021 | 13,917 | 50,304 |
| Personal Wealth | 9,194 | 39,248 | 10,325 | 45,313 |
| Real Property | 0.34 | 0.47 | 0.36 | 0.48 |
| Female | 0.44 | 0.50 | 0.44 | 0.50 |
| Age $<$25 | 0.03 | 0.18 | 0.01 | 0.08 |
| Age 25-35 | 0.21 | 0.40 | 0.17 | 0.37 |
| Age 46-55 | 0.17 | 0.37 | 0.18 | 0.39 |
| Age 56-65 | 0.14 | 0.35 | 0.14 | 0.35 |
| Age 66-75 | 0.14 | 0.35 | 0.16 | 0.37 |
| Age $>$75 | 0.08 | 0.27 | 0.11 | 0.31 |
| University | 0.19 | 0.39 | 0.21 | 0.40 |
| Employed | 0.58 | 0.49 | 0.57 | 0.50 |
| Self-Employed | 0.06 | 0.24 | 0.07 | 0.25 |
| Retired | 0.30 | 0.46 | 0.33 | 0.47 |
| Married | 0.28 | 0.45 | 0.29 | 0.45 |
| Separated | 0.42 | 0.49 | 0.45 | 0.50 |
| Adults | 1.66 | 0.72 | 1.64 | 0.74 |
| Children | 0.38 | 0.76 | 0.34 | 0.70 |
| Concerned | | | | |
| - very concerned | 30.40 | 0.46 | 28.01 | 0.45 |
| - somewhat concerned | 50.42 | 0.50 | 48.82 | 0.49 |
| - not concerned at all | 19.18 | 0.39 | 23.17 | 0.42 |
| East Germany | 0.28 | 0.45 | 0.28 | 0.45 |

Number of individuals in the panel, N = 2,628

Table 2.5: The effects of financial risk aversion on “naive” diversification

The table reports marginal effects after multinomial logit regression. The dependent variable is a categorical variable that takes four successive values, corresponding to the number of asset classes held in a portfolio. Variable *FRA* indicates the degree of financial risk aversion and takes values from 0 (lowest risk aversion) to 10 (highest risk aversion). *Household Wealth 40p* through *Household Wealth 100p* are dummy variables indicating respective wealth percentiles. *Household Wealth 20p* denotes the lowest 20-percentile and is the base category. *Age*$\geq$ 25 through *Age*$>$ 75 are age group dummies with *Age* 46-55 being the base category. *Probability of outcome* is the predicted probability of holding a given number of asset types. The marginal effects and predicted probabilities are calculated at FRA = 5, while continuous variables are held at their means and dummy- and count-variables at 0. Cluster robust standard errors are reported in parentheses. Levels of significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

| | $N_{assets} = 0$ | $N_{assets} = 1$ | $N_{assets} = 2$ | $N_{assets} = 3$ | $N_{assets} \geq 4$ |
|---|---|---|---|---|---|
| FRA | 0.004** | 0.010*** | 0.004 | -0.008** | -0.010*** |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| ln(Household Income) | -0.094*** | -0.145*** | -0.026 | 0.143*** | 0.123*** |
| | (0.011) | (0.015) | (0.017) | (0.017) | (0.015) |
| Household Wealth 40p (d) | -0.076*** | 0.018 | 0.053 | -0.004 | 0.009 |
| | (0.011) | (0.030) | (0.036) | (0.037) | (0.038) |
| Household Wealth 60p (d) | -0.101*** | -0.039* | -0.003 | 0.051* | 0.092*** |
| | (0.013) | (0.020) | (0.025) | (0.026) | (0.027) |
| Household Wealth 80p (d) | -0.070*** | -0.036 | 0.006 | 0.030 | 0.070** |
| | (0.014) | (0.023) | (0.028) | (0.030) | (0.028) |
| Household Wealth 100p (d) | -0.054*** | -0.054** | -0.067** | 0.041 | 0.134*** |
| | (0.015) | (0.025) | (0.028) | (0.033) | (0.034) |
| ln(Personal Wealth) | -0.007*** | -0.007*** | -0.001 | 0.006*** | 0.009*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| Real Property (d) | -0.024** | -0.048*** | -0.002 | 0.041* | 0.033** |
| | (0.012) | (0.017) | (0.019) | (0.022) | (0.017) |
| Female (d) | 0.017** | 0.012 | 0.045*** | -0.025 | -0.049*** |
| | (0.009) | (0.013) | (0.015) | (0.015) | (0.013) |
| Age <25 (d) | 0.004 | -0.065** | -0.052 | 0.012 | 0.101* |
| | (0.028) | (0.031) | (0.042) | (0.051) | (0.058) |
| Age 25-35 (d) | -0.015 | -0.025 | -0.026 | 0.012 | 0.055*** |
| | (0.011) | (0.019) | (0.020) | (0.021) | (0.019) |
| Age 36-45 (d) | 0.018 | 0.071*** | -0.002 | -0.048** | -0.038** |
| | (0.013) | (0.024) | (0.022) | (0.020) | (0.015) |
| Age 56-65 (d) | 0.004 | 0.130*** | 0.010 | -0.093*** | -0.050*** |
| | (0.015) | (0.029) | (0.026) | (0.023) | (0.017) |
| Age 66-75 (d) | 0.008 | 0.190*** | 0.033 | -0.152*** | -0.079*** |
| | (0.020) | (0.041) | (0.037) | (0.027) | (0.021) |
| Age >75 (d) | 0.013 | 0.327*** | -0.054 | -0.158*** | -0.128*** |
| | (0.023) | (0.048) | (0.037) | (0.029) | (0.016) |
| University (d) | -0.031*** | -0.022 | -0.007 | 0.032* | 0.028* |
| | (0.011) | (0.017) | (0.018) | (0.018) | (0.015) |
| Employed (d) | -0.056*** | -0.034** | -0.010 | 0.080*** | 0.021 |
| | (0.011) | (0.017) | (0.020) | (0.021) | (0.018) |
| Self-Employed (d) | 0.032 | 0.013 | -0.007 | -0.042* | 0.005 |
| | (0.022) | (0.027) | (0.025) | (0.025) | (0.020) |
| Retired (d) | -0.022 | -0.013 | 0.002 | 0.073** | -0.040* |
| | (0.015) | (0.025) | (0.030) | (0.035) | (0.024) |
| Married (d) | -0.014 | 0.008 | 0.002 | -0.014 | 0.018 |
| | (0.013) | (0.021) | (0.022) | (0.022) | (0.018) |
| Separated (d) | 0.038*** | 0.024 | 0.032 | -0.053*** | -0.042** |
| | (0.013) | (0.018) | (0.021) | (0.020) | (0.017) |
| Adults | 0.019*** | 0.006 | -0.006 | -0.017 | -0.002 |
| | (0.007) | (0.011) | (0.013) | (0.013) | (0.010) |
| Children | 0.022*** | 0.026*** | 0.002 | -0.023** | -0.028*** |
| | (0.006) | (0.010) | (0.011) | (0.011) | (0.008) |
| Concerned | -0.025*** | -0.025*** | 0.002 | 0.022** | 0.026*** |
| | (0.006) | (0.008) | (0.010) | (0.010) | (0.008) |
| East Germany (d) | -0.020** | -0.016 | 0.022 | -0.002 | 0.016 |
| | (0.009) | (0.014) | (0.016) | (0.017) | (0.015) |
| Year Dummies | Yes | Yes | Yes | Yes | Yes |
| Probability of outcome | 0.10 | 0.20 | 0.29 | 0.27 | 0.14 |

Probability($\chi^2$) = 0.00, Log-Likelihood = -14052, Pseudo-$R^2$ = 0.16, $N_{obs}$ = 10,512

Table 2.6: The effects of *financial* risk aversion on "sophisticated" diversification

The table reports marginal effects after multinomial logit regression. The dependent variable is a categorical variable that takes eight different values corresponding to the seven portfolio types defined in Section 3.2.2 plus the category "no assets". Variable *FRA* indicates the degree of financial risk aversion and takes values from 0 (lowest risk aversion) to 10 (highest risk aversion). *Household Wealth 40p* through *Household Wealth 100p* are dummy variables indicating respective wealth percentiles. *Household Wealth 20p* denotes the lowest 20-percentile and is the base category. *Age*$\geq$ 25 through *Age*$>$ 75 are age group dummies with *Age* 46-55 being the base category. *Probability of outcome* is the predicted probability of holding a given number of asset types. The marginal effects and predicted probabilities are calculated at FRA = 5, while continuous variables are held at their means and dummy- and count-variables at 0. Cluster robust standard errors are reported in parentheses. Levels of significance: $^{*}p < 0.10$,$^{**}$ $p < 0.05$,$^{***}$ $p < 0.01$.

| | | Undiversified | | | Quite diversified | | | Fully diversified |
|---|---|---|---|---|---|---|---|---|
| | No assets | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 | Type 7 |
| FRA | 0.005*** | 0.017*** | 0.001 | -0.004*** | 0.012*** | -0.008*** | -0.003*** | -0.019*** |
| | (0.002) | (0.003) | (0.001) | (0.001) | (0.004) | (0.003) | (0.001) | (0.004) |
| ln(Household Income) | -0.101*** | -0.153*** | -0.013*** | -0.004 | 0.019 | 0.009 | 0.019*** | 0.224*** |
| | (0.011) | (0.016) | (0.005) | (0.004) | (0.019) | (0.012) | (0.005) | (0.020) |
| Household Wealth 40p (d) | -0.078*** | 0.064* | -0.020*** | -0.006 | 0.021 | 0.011 | 0.003 | 0.006 |
| | (0.011) | (0.033) | (0.006) | (0.007) | (0.038) | (0.029) | (0.012) | (0.045) |
| Household Wealth 60p (d) | -0.103*** | 0.009 | -0.025*** | -0.003 | -0.024 | 0.062** | 0.006 | 0.078** |
| | (0.014) | (0.022) | (0.007) | (0.006) | (0.028) | (0.026) | (0.008) | (0.031) |
| Household Wealth 80p (d) | -0.073*** | -0.020 | -0.012* | 0.004 | -0.031 | 0.054* | 0.010 | 0.067* |
| | (0.015) | (0.024) | (0.007) | (0.007) | (0.031) | (0.029) | (0.009) | (0.035) |
| Household Wealth 100p (d) | -0.059*** | -0.066*** | -0.002 | -0.002 | -0.069** | 0.050 | 0.015* | 0.134*** |
| | (0.016) | (0.025) | (0.008) | (0.007) | (0.034) | (0.033) | (0.009) | (0.040) |
| ln(Personal Wealth) | -0.008*** | -0.006*** | -0.002*** | -0.001 | -0.003 | 0.005*** | -0.000 | 0.015*** |
| | (0.001) | (0.002) | (0.000) | (0.000) | (0.002) | (0.002) | (0.001) | (0.003) |
| Real Property (d) | -0.020* | -0.002 | -0.012** | 0.003 | 0.045** | -0.008 | -0.001 | -0.003 |
| | (0.012) | (0.018) | (0.005) | (0.005) | (0.023) | (0.014) | (0.005) | (0.023) |
| Female (d) | 0.018** | 0.007 | 0.004 | 0.011** | 0.014 | -0.004 | 0.002 | -0.052*** |
| | (0.009) | (0.014) | (0.004) | (0.005) | (0.017) | (0.011) | (0.004) | (0.017) |
| Age $<$25 (d) | 0.001 | -0.043 | -0.008 | 0.013 | -0.104** | -0.014 | 0.028 | 0.128* |
| | (0.028) | (0.034) | (0.010) | (0.017) | (0.044) | (0.031) | (0.035) | (0.067) |
| Age 25-35 (d) | -0.017 | -0.001 | -0.009 | -0.003 | -0.031 | 0.024 | -0.007 | 0.043* |
| | (0.012) | (0.021) | (0.006) | (0.005) | (0.022) | (0.018) | (0.005) | (0.024) |
| Age 36-45 (d) | 0.019 | 0.058** | 0.017* | 0.006 | -0.044** | -0.020 | 0.002 | -0.038* |
| | (0.014) | (0.025) | (0.009) | (0.007) | (0.022) | (0.015) | (0.005) | (0.022) |
| Age 56-65 (d) | 0.005 | 0.135*** | 0.021* | -0.010** | -0.046* | 0.000 | -0.003 | -0.102*** |
| | (0.016) | (0.033) | (0.011) | (0.004) | (0.027) | (0.021) | (0.006) | (0.023) |
| Age 66-75 (d) | 0.004 | 0.218*** | 0.002 | 0.009 | -0.124*** | 0.021 | -0.005 | -0.124*** |
| | (0.021) | (0.046) | (0.011) | (0.015) | (0.032) | (0.031) | (0.008) | (0.030) |
| Age $>$75 (d) | 0.008 | 0.345*** | -0.019*** | 0.001 | -0.141*** | -0.015 | -0.014*** | -0.164*** |
| | (0.023) | (0.053) | (0.007) | (0.011) | (0.034) | (0.026) | (0.005) | (0.028) |
| University (d) | -0.033*** | -0.029 | -0.001 | 0.009 | -0.046** | 0.016 | 0.019*** | 0.063*** |
| | (0.011) | (0.018) | (0.006) | (0.007) | (0.019) | (0.013) | (0.007) | (0.021) |
| Employed (d) | -0.056*** | -0.022 | -0.003 | -0.013** | 0.043** | 0.031* | -0.006 | 0.025 |
| | (0.011) | (0.017) | (0.006) | (0.006) | (0.021) | (0.018) | (0.009) | (0.024) |
| Self-Employed (d) | 0.029 | -0.055** | 0.009 | 0.017 | -0.058** | 0.040 | 0.020** | -0.001 |
| | (0.023) | (0.023) | (0.009) | (0.010) | (0.027) | (0.025) | (0.009) | (0.029) |
| Retired (d) | -0.022 | -0.007 | -0.000 | -0.016** | 0.045 | 0.035 | -0.010 | -0.025 |
| | (0.016) | (0.026) | (0.008) | (0.008) | (0.034) | (0.029) | (0.009) | (0.035) |
| Married (d) | -0.016 | -0.019 | 0.013 | 0.002 | 0.021 | -0.013 | 0.002 | 0.010 |
| | (0.013) | (0.021) | (0.008) | (0.006) | (0.026) | (0.015) | (0.006) | (0.025) |
| Separated (d) | 0.039*** | -0.006 | 0.012* | 0.008 | 0.041* | -0.014 | -0.002 | -0.078*** |
| | (0.013) | (0.018) | (0.006) | (0.006) | (0.023) | (0.014) | (0.006) | (0.023) |
| Adults | 0.023*** | 0.021* | -0.001 | -0.001 | 0.011 | -0.014 | -0.006 | -0.034** |
| | (0.007) | (0.012) | (0.004) | (0.003) | (0.013) | (0.009) | (0.004) | (0.014) |
| Children | 0.027*** | 0.032*** | 0.008** | -0.002 | 0.008 | -0.022** | -0.006** | -0.046*** |
| | (0.006) | (0.011) | (0.003) | (0.003) | (0.012) | (0.010) | (0.003) | (0.012) |
| Concerned | -0.027*** | -0.021** | -0.006* | 0.003 | -0.011 | 0.013* | 0.003 | 0.045*** |
| | (0.006) | (0.009) | (0.003) | (0.003) | (0.010) | (0.007) | (0.003) | (0.011) |
| East Germany (d) | -0.023*** | -0.012 | -0.008** | -0.003 | 0.021 | -0.007 | 0.004 | 0.029 |
| | (0.009) | (0.014) | (0.004) | (0.004) | (0.018) | (0.012) | (0.005) | (0.020) |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Probability of outcome | 0.10 | 0.20 | 0.03 | 0.01 | 0.32 | 0.09 | 0.02 | 0.24 |

Probability($\chi^2$) = 0.00, Log-Likelihood = -15178, Pseudo-$R^2$ = 0.17, $N_{obs}$ = 10512

## Table 2.7: The effects of the number of safe assets on the number of risky assets held

The table reports marginal effects after multinomial logit regression. The dependent variable is a categorical variable that takes three successive values from 0 to 2, according to the number of risky assets in a portfolio. Variable *FRA* indicates the degree of financial risk aversion and takes values from 0 (lowest risk aversion) to 10 (highest risk aversion). $N_{safe\,assets}$ is a count variable indicating the number of safe assets in a portfolio. *Household Wealth 40p* through *Household Wealth 100p* are dummy variables indicating respective wealth percentiles. *Household Wealth 20p* denotes the lowest 20-percentile and is the base category. *Age*$\geq$ 25 through *Age*$>$ 75 are age group dummies with *Age* 46-55 being the base category. *Probability of outcome* is the predicted probability of holding a given number of asset types.

The marginal effects and predicted probabilities are calculated at FRA = 5, while continuous variables are held at their means and dummy- and count-variables at 0. Cluster robust standard errors are reported in parentheses. Levels of significance: $^{*}p < 0.10$,$^{**}$ $p < 0.05$,$^{***}$ $p < 0.01$.

| | no risky assets | one risky asset | two risky assets |
|---|---|---|---|
| FRA | 0.033*** | -0.031*** | -0.001*** |
| | (0.003) | (0.003) | (0.000) |
| $N_{safe\,assets}$ | -0.094*** | 0.088*** | 0.006*** |
| | (0.006) | (0.006) | (0.001) |
| ln(Household Income) | -0.199*** | 0.188*** | 0.011*** |
| | (0.015) | (0.015) | (0.002) |
| Household Wealth 40p (d) | -0.037 | 0.034 | 0.003 |
| | (0.031) | (0.031) | (0.006) |
| Household Wealth 60p (d) | -0.131*** | 0.134*** | -0.002 |
| | (0.023) | (0.023) | (0.004) |
| Household Wealth 80p (d) | -0.128*** | 0.129*** | -0.001 |
| | (0.026) | (0.026) | (0.004) |
| Household Wealth 100p (d) | -0.181*** | 0.182*** | -0.001 |
| | (0.029) | (0.029) | (0.002) |
| ln(Personal Wealth) | -0.015*** | 0.013*** | 0.002*** |
| | (0.002) | (0.002) | (0.001) |
| Real Property (d) | 0.020 | -0.018 | -0.002 |
| | (0.017) | (0.016) | (0.002) |
| Female (d) | 0.032*** | -0.029** | -0.003* |
| | (0.012) | (0.012) | (0.002) |
| Age <25 (d) | -0.138*** | 0.151*** | -0.012*** |
| | (0.050) | (0.050) | (0.002) |
| Age 25-35 (d) | -0.048*** | 0.048*** | -0.000 |
| | (0.019) | (0.018) | (0.002) |
| Age 36-45 (d) | 0.020 | -0.015 | -0.004*** |
| | (0.019) | (0.018) | (0.002) |
| Age 56-65 (d) | 0.080*** | -0.073*** | -0.007*** |
| | (0.021) | (0.021) | (0.002) |
| Age 66-75 (d) | 0.041 | -0.038 | -0.003 |
| | (0.031) | (0.031) | (0.003) |
| Age >75 (d) | 0.126*** | -0.124*** | -0.002 |
| | (0.029) | (0.028) | (0.005) |
| University (d) | -0.098*** | 0.088*** | 0.009*** |
| | (0.015) | (0.015) | (0.003) |
| Employed (d) | -0.021 | 0.024 | -0.003 |
| | (0.020) | (0.020) | (0.003) |
| Self-Employed (d) | -0.081*** | -0.006 | 0.088*** |
| | (0.028) | (0.023) | (0.019) |
| Retired (d) | 0.018 | -0.009 | -0.009** |
| | (0.029) | (0.029) | (0.004) |
| Married (d) | 0.008 | -0.011 | 0.003 |
| | (0.019) | (0.018) | (0.003) |
| Separated (d) | 0.072*** | -0.072*** | 0.000 |
| | (0.017) | (0.016) | (0.002) |
| Adults | 0.050*** | -0.048*** | -0.002 |
| | (0.011) | (0.011) | (0.001) |
| Children | 0.065*** | -0.062*** | -0.002** |
| | (0.010) | (0.010) | (0.001) |
| Concerned | -0.056*** | 0.055*** | 0.001 |
| | (0.009) | (0.009) | (0.001) |
| East Germany (d) | -0.019 | 0.018 | 0.002 |
| | (0.014) | (0.013) | (0.002) |
| Year Dummies | Yes | Yes | Yes |
| Probability of outcome | 0.68 | 0.31 | 0.01 |

Probability($\chi^2$) = 0.00, Log-Likelihood = -5186, Pseudo-$R^2$ = 0.26, $N_{obs}$ = 10512

## Table 2.8: The effects of financial risk aversion on "naive" diversification

The table reports marginal effect of the financial risk aversion FRA on the probability of holding a given number of asset types in a portfolio. The effects are estimated by means of multinomial logit regression. The estimation is performed on a sub-sample of people with wealth exceeding the sample median of 8,000 Euro, and on a sub-sample of people with wealth exceeding the 75th percentile of 134,000 Euro. Other control variables included in the regression (but not reported) are: the logarithm of the household total wealth and the individualsŠ personal wealth, age and age squared, binary indicators of gender, higher education, employment status, ownership of residential property, marital status and the number of adults and children in a household. The marginal effects and predicted probabilities are calculated at FRA = 5. Cluster robust standard errors are reported in parentheses. Levels of significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

| | $N_{assets} = 0$ | $N_{assets} = 1$ | $N_{assets} = 2$ | $N_{assets} = 3$ | $N_{assets} \geq 4$ | $N_{assets} \geq 5$ | $N_{assets} \geq 6$ |
|---|---|---|---|---|---|---|---|
| People with wealth > sample median, N =5,177 | | | | | | | |
| FRA | 0.005** | 0.010*** | 0.001 | -0.003 | -0.012*** | -0.002** | -0.000** |
| Probability of outcome | 0.06 | 0.17 | 0.29 | 0.30 | 0.14 | 0.04 | <0.01 |
| People with wealth > 75th percentile, N =2,628 | | | | | | | |
| FRA | -0.000 | 0.003 | 0.006 | 0.005 | -0.012*** | -0.002 | -0.000 |
| Probability of outcome | 0.06 | 0.14 | 0.25 | 0.32 | 0.16 | 0.05 | <0.01 |

## Table 2.9: The effects of *financial* risk aversion on "sophisticated" diversification

The table reports marginal effect of the financial risk aversion FRA on the probability of holding a given portfolio type as defined in Section 3.2.2 plus the category "no assets". The effects are estimated by means of multinomial logit regression. The estimation is performed on a sub-sample of people with wealth exceeding the sample median of 8,000 Euro, and on a sub-sample of people with wealth exceeding the 75th percentile of 134,000 Euro. Other control variables included in the regression (but not reported) are: the logarithm of the household total wealth and the individualsŠ personal wealth, age and age squared, binary indicators of gender, higher education, employment status, ownership of residential property, marital status and the number of adults and children in a household. The marginal effects and predicted probabilities are calculated at FRA = 5. Cluster robust standard errors are reported in parentheses. Levels of significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

| | | Undiversified | | | Quite diversified | | | Fully diversified |
|---|---|---|---|---|---|---|---|---|
| | No assets | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 | Type 7 |
| People with wealth > sample median, N =5,177 | | | | | | | | |
| FRA | 0.005*** | 0.017*** | 0.000 | -0.002*** | 0.014*** | -0.007*** | -0.003*** | -0.024*** |
| Probability of outcome | 0.06 | 0.18 | 0.02 | 0.01 | 0.32 | 0.09 | 0.02 | 0.27 |
| People with wealth > 75th percentile, N =2,628 | | | | | | | | |
| FRA | - 0.000 | 0.010*** | 0.000 | -0.000 | 0.026*** | -0.008*** | -0.004*** | -0.026*** |
| Probability of outcome | 0.06 | 0.15 | 0.03 | < 0.01 | 0.33 | 0.07 | 0.02 | 0.33 |

## Table 2.10: The effects of the number of safe assets on the number of risky assets held

The table reports marginal effects of the financial risk aversion FRA and the number of risk-free assets on the probability of holding a given number of risky assets. The effect is estimated by means of multinomial logit regression. The estimation is performed on a sub-sample of people with wealth exceeding the sample median of 8,000 Euro, and on a sub-sample of people with wealth exceeding the 75th percentile of 134,000 Euro. Other control variables included in the regression (but not reported) are: the logarithm of the household total wealth and the individualsŠ personal wealth, age and age squared, binary indicators of gender, higher education, employment status, ownership of residential property, marital status and the number of adults and children in a household. The marginal effects and predicted probabilities are calculated at FRA = 5. Cluster robust standard errors are reported in parentheses. Levels of significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

| | no risky assets | one risky asset | two risky assets |
|---|---|---|---|
| People with wealth > sample median, N =5,177 | | | |
| FRA | 0.037*** | -0.035*** | -0.002*** |
| $N_{safe\,assets}$ | -0.091*** | 0.085*** | 0.005*** |
| Probability of outcome | 0.62 | 0.37 | 0.01 |
| People with wealth > 75th percentile, N =2,628 | | | |
| FRA | 0.037*** | -0.034*** | -0.003*** |
| $N_{safe\,assets}$ | -0.107*** | 0.103*** | 0.006 |
| Probability of outcome | 0.58 | 0.41 | 0.01 |

# Chapter 3

# Effects of Individuals' Risk Attitude and Gender on the Financial Risk-Taking: Evidence from National Surveys of Household Finance

*Joint work with Oleg Badunenko and Dorothea Schäfer*

***Abstract***: This study investigates the role of gender in individuals' financial risk taking. We find that although females exhibit, on average, lower risk propensity than males, the effect of gender on the actual risk taking varies across countries and across types of financial decisions. Specifically, we find that gender-based differences in the risk taking depend on the level of gender equality in a given society. Where gender inequality is substantial, females are less likely to invest in risky assets than males even when their willingness to take financial risks is equal. Furthermore, we find no gender effects on the portfolio share of wealth allocated to risky assets in all countries but the one with the highest gender inequality.

***JEL***: G11, J16
***Keywords***: gender, risk aversion, financial behavior

## 3.1 Introduction

It is commonly believed that men are more willing to take bigger risks than women when it comes to investment decisions. Despite its popularity, this belief is not substantiated in the academic literature. In particular, a number of recent studies find either no effects of gender on the risk propensity (Tanaka et al., 2010) or show that the effects are highly sensitive to other factors such as framing of financial decisions (Schubert et al., 1999) or cultural environment (Finucane et al., 2000; Booth and Nolen, 2009). Given that cultural factors are indeed an important determinant of gender differences in the financial risk-taking, evidence generated based on a sample of individuals with the same cultural background should not be automatically generalized for the rest of the world. In light of this, and taking into account that almost all empirical evidence on gender differences in the financial risk propensity existing so far is derived using data from the United States, an analysis of gender effects in a cross-country framework is warranted.

This study contributes to the stream of literature investigating the role of cultural determinants in the financial behavior of males and females. Specifically, we provide evidence on the financial risk-taking of males and females in four different European countries: Austria, the Netherlands, Italy and Spain. According to the 2009 Global Gender Gap Report, the four European countries considered in this study exhibit substantial differences in the degree of gender equality. The extent of gender equality is measured though gender-based differences in access to resources and opportunities in four domains of social life: participation in the labor markets and earnings, educational attainment, political empowerment and health and survival.[1] Specifically, in the ranking of 134 countries, the Netherlands and Spain come on the 11th and the 17th position respectively, closely followed by Austria on the 20th position. Italy comes in at 72th position, substantially below the other three countries. Insufficient gender equality implies asymmetric social roles and opportunities for males and females that may lead to gender differences in financial behavior. The aim of the study is to determine whether gender differences in the financial risk taking depends on the extent of gender equality in a given society. *Ceteris paribus*, we expect to find that differences in risk taking between men and women are the greatest in countries where gender inequality is more pronounced. The empirical test of this conjecture relies on micro-level data from the four European countries collected via representative national surveys.

Our approach to measure the extent of risk taken is closely related to methodology applied in previous studies. In particular, Jianakoplos and Bernasek (1998), Bajtelsmit et al. (1999), and Bernasek and Shwiff (2001) measure the degree of individual risk propensity by the share of risky assets in an investor's financial portfolio. Because a large fraction of people have no risky assets, the researchers estimate the effect of gender using a Tobit estimation. However, this technique does not take into account the potential sample-selection bias. This bias is likely to emerge when decision to hold risky assets and decision about the amount of these assets are correlated through observed or unobserved common factors. To remedy this problem, we apply a sample-selection regression model using a Heckman two-stage estimation procedure. Apart from its pure technical advantage, this approach allows

[1] http://www.weforum.org/pdf/gendergap/report2009.pdf

us to shed some light on two different aspects of risk taking, namely, the decision to acquire risky assets and the decision about what fraction of wealth to invest in these assets. The two aspects of risk taking represent two different types of portfolio decisions – the ownership decision and the allocation decision – and there are, *a priori*, no reasons to believe that gender identically affects both. Gender differences, with respect to the ownership decision, are likely to occur because males and females differ significantly with respect to factors that determine the ownership decision (e.g. females are on average less wealthy and more risk averse than males). Hence, it is plausible to expect that females are less likely to own risky assets. In contrast, the relationship between gender and allocation decision is not that straightforward. On the one hand, gender-specific distributions of wealth or risk preferences among individuals holding risky assets may be different, thus leading to differences in the portfolio shares of risky assets. On the other hand, if certain levels of wealth and risk propensity are prerequisites for ownership of risky assets, then males and females who hold such assets should exhibit more similarities with each other than males and females in the population at large. Hence, conditional on ownership, the difference between males and females regarding the portfolio share allocated to risky assets may be small.

Our results suggest that gender-based differences in financial risk taking vary across countries and types of financial decisions. While females are found to be less willing to invest in risky assets than males in all four countries considered, the discrepancy in actual risk taking is less pronounced in some countries than in others. In particular, we find that in the country with relatively high gender inequality, females are less likely to hold risky assets than males even if they report equal willingness to take risks. In contrast, in countries with relatively high gender equality, males and females who have equal risk preferences are equally likely to hold risky financial assets in their portfolios. Furthermore, in these countries gender seems to have no effect on the decision over what share of the portfolio is invested in risky assets. Hence, the popular belief that females are less risk prone than males in all instances does not hold. A special case presents the country with relatively high gender inequality. Here, females are found to allocate smaller portfolio shares to risky assets than males, given that they own some risky assets.

The remainder of the paper is organized as follows. In the next section, we review literature investigating gender-specific behavior in financial risk-taking. In Section 3, we formulate our working hypotheses and describe how the hypotheses are tested. Data are described in Section 4. In Section 5, we analyze the effects of gender on the two types of portfolio decisions: ownership of risky assets and allocation of wealth to these assets. The last section concludes.

## 3.2 What Does the Literature Say About the Role of Gender in Investment Decisions?

Academic research on the role of gender in financial risk-taking was boosted in the 1990s when the ever increasing participation of private households in financial markets motivated scholars and practitioners to look for the determinants of individual investment decisions. A growing amount of household data collected by private and government sponsored surveys in the USA provided first insights into the financial portfolios of private investors and allowed investigating whether males and females differ with respect to risk taking in investment decisions. For instance, the Survey of Consumer Finances (SCF), financed by the Federal Reserve Board, collected detailed information on the composition of households' financial portfolios. Relying on these data, a number of studies provide evidence of significant gender differences in investment decisions.

Sunden and Surette (1998), who examine the composition of defined contribution plans, show that males are more likely to hold stocks than females. Bajtelsmit et al. (1999) and Jianakoplos and Bernasek (1998), who focus on the division of wealth between risky and risk-free assets, find that gender differences are also present with respect to portfolio allocation. According to the results, females tend to allocate a smaller fraction of their wealth to risky assets than males. A study of investment decisions by staff at the University of Colorado, conducted by Bernasek and Shwiff (2001), confirms the results of the previous studies. Furthermore, a number of experimental studies that elicited individuals' risk aversion parameters from investment choices in hypothetical lotteries also find that women are more risk-averse than males (Powell and Ansic, 1997; Hartog et al., 2002; Fellner and Maciejovsky, 2007; Eckel and Grossman, 2008). All in all, a common belief about significant gender differences in financial risk taking seemed to find unanimous confirmation by academic research. Moreover, the fact that none of the socioeconomic investor-specific attributes considered in the analyzes explains the gender gap in portfolio decisions boosted the opinion that gender differences in risk preferences stem from psychological and cognitive attributes innate to gender (Croson and Gneezy (2009)).

However, several recent studies have challenged the generality of previous findings. In particular, Schubert et al. (1999) shows that contextual framing of experiments has a paramount effect on the risk-taking behavior of males and females. When lotteries are framed as gains, males are more risk loving than females; however, when lotteries are framed in terms of losses, then males are more risk averse than females. Furthermore, Tanaka et al. (2010) tests gender differences in risk preferences using the theoretical framework of prospect theory. According to their findings, gender has no influence on individual risk preferences.

The inconclusive evidence on risk taking by males and females raises an important question: Could gender differences in financial behavior be caused by some factors that were not identified by previous research? One factor that may facilitate differential behavior of males and females is culture. Cultural factors, represented by collective values and norms, shape individual behavior in various domains of life and may also affect individual financial behavior (Carroll et al., 1994; Fernández and Fogli, 2006; Giuliano, 2007). Hence, collective norms that foster disparate social roles and opportunities of males and females may also be the cause of gender differences in investment behavior. The first study specifically focusing on gender-specific risk-taking behavior in groups with different cultural background is by Finucane et al. (2000). An important finding of the study is that gender differences vary significantly across ethnic groups. Another notable study by Booth and Nolen (2009) shows that girls from all-girl schools are as likely to choose a risky gamble as boys from either coed or all-male schools, as opposed to girls from coed schools. The findings of the two studies indicate that cultural factors may indeed play an important role in the extent of risk taking by males and females. This also motivates further research of this relationship.

This study contributes to the stream of literature investigating the role of cultural determinants in the financial behavior of males and females. We make the first attempt to provide international evidence on gender differences in financial risk taking. While closely related to the existing survey-based literature on gender differences represented by Bajtelsmit et al. (1999), Jianakoplos and Bernasek (1998) and Bernasek and Shwiff (2001), we extend the methodology used in these studies and apply it to the measurement of risk taking by males and females in four European countries. *Ceteris paribus*, we expect to find that differences in risk taking between men and women are the greatest in the country in which the gender roles in society are most pronounced.

## 3.3 Methodology of the Analysis

The aim of the paper is to test whether, in each of the four considered European countries, males take more financial risks than females. Our methodology of measurement of risk taking relies upon the approach developed by Friend and Blume (1975). According to this approach an individual's propensity for risk taking is reflected in the division of a financial portfolio between risky and risk-free assets. The higher the proportion of net worth invested in risky assets the more risk-prone an individual is. Empirical studies adopting this approach must address the fact that many individuals do not own any risky assets at all. Jianakoplos and Bernasek, 1998; Bernasek and Shwiff, 2001 deal with this problem by fitting data to a censored regression model and using Tobit estimation technique. This estimation methodology relies on the assumption that for any investor there should be a positive amount of risky assets that is optimal for his/her portfolio. However, according to Haliassos and Bertaut (1995), an investor will not hold any risky assets if the utility gained from ownership of the optimal amount is smaller than the incurred participation costs. Hence, holdings of risky assets are observed only for some investors, while it is censored at zero for the rest.

However, it is arguable that the Tobit estimation technique will produce biased results when applied to the portfolio decisions of private investors. This bias is likely to emerge when the decision to hold risky assets and the decision about the amount of these assets are correlated either through observable characteristics of individuals or via some unobserved common factors. A censored regression model does not take into account this correlation. For example, one of such factors is individual financial knowledge, which surely affects both decisions but is rarely observed by researchers. Thus, a more suitable model in this case is a sample-selection model that models portfolio decisions in a two-step procedure. In the first step, researchers investigate the ownership decision by estimating the probability of investing in risky assets. Then, the allocation decision is analyzed by taking into account the results obtained for the ownership decision. We apply this approach in our analysis using the Heckman estimation procedure in order to account for the possible correlation between the two stages of investment decision.[2]

The two-stage approach allows us to test two hypotheses regarding the propensity for risk taking of males and females. The first hypothesis relates to the decision about ownership of risky assets and reads :

*Males are more likely to own some risky assets than females, ceteris paribus.*

The second hypothesis is related to the allocation decision:

*Males allocate a larger fraction of their financial portfolios to risky assets than females, ceteris paribus.*

The effect of gender on the ownership decision represents the first step of a portfolio decision and is estimated using a probit regression model. The dependent variable in this model is a binary-variable equaling 1 if an investor owns some risky assets and 0 otherwise. The effect of gender is captured by a binary-variable *Male* equal to 1 if an investor is male and 0 if female. A positive and statistically significant coefficient on this variable would indicate that, *ceteris paribus*, men are more likely to invest in risky financial assets than women. The first step of the Heckman estimation procedure is a probit model, used to generate Mills ratio. The ratio is then included as an explanatory variable in the second step model representing the allocation decision. In this model, the dependent variable shows the fraction of financial wealth allocated to risky assets. It is a continuous variable with values in the interval (0,1]. Here, the estimated coefficient of the variable *Male* would show whether males tend to hold larger shares of risky assets than females.

[2]The two-stage approach to the modeling of portfolio decisions by private investors is increasingly applied in empirical studies of household finances. See for example Guiso et al. (2003), Guiso et al. (2002).

## 3.4 Data

### 3.4.1 Data Sets and Unit of Observation

To test our hypotheses we rely on cross-sectional data on household finance collected by four representative national surveys of Austria, the Netherlands, Italy and Spain. Only these four countries are considered because no other European country collects all the data required for this analysis. Specifically, other national surveys of household finance do not allow the identification of which partner is responsible for investment decisions by couples; furthermore, the surveys do not collect information about individual risk preferences of respondents.

The Austrian Survey of Household Financial Wealth was conducted by Oesterreichische Nationalbank in 2004.[3] The sample comprises 2,556 households. Wealth data were collected at the household level. The Dutch Household Survey (DHS) is an annual survey conducted by CentERdata since 1993.[4] We use the 2004 survey wave that covers 2,187 households. All data, including information on wealth, were collected at the individual level. The Italian Survey of Household Income and Wealth (SHIW) is conducted by the Bank of Italy every two years since 2002.[5] For this study we use the 2004 survey wave, with a sample of 8,012 households. Wealth data were collected at the household level. The Spanish Survey of Household Finances (EFF) is conducted by Banco de Espñia every three years since 2002.[6] We use the 2005 survey wave. The sample comprises of 5,962 households. Wealth data are collected at the household level.

Using household-level data raises an important question about who makes investment decisions in multi-person households. Ideally, one should identify who is responsible for investment decisions, as is done by Bernasek and Shwiff (2001). We can identify decision-makers with different accuracy depending on survey. For instance, the most accurate identification is possible in the Dutch survey. Couples were asked how they decide on financial matters. A member who answered that he/she has the most or full control over the financial decisions was coded as decision-maker. If both members of a couple told that each of them manages own money, we coded both individuals as decision-makers. When couples could not tell who of them has more influence on financial decisions, we relied on the indicator-variable "household head" that was assigned to respondents by the organizers of the survey based on respondents' earnings and knowledge about their households' budget. In the Austrian Survey, a person was coded as decision-maker if he/she was indicated by the surveyors

[3] More details on the survey can be found in Beer, Mooslechner, Schürz and Wagner (2009): Austrian Households' Financial Wealth: An Analysis Based on Microeconomic Data. ONB Monetary Policy & Economy Q2/06.

[4] Additional information about the survey is available at the CentERdata web page, http://centerdata.nl

[5] Survey information is available at http://www.bancaditalia.it/statistiche/indcamp/bilfait

[6] A survey description is found in Bover (2004): The Spanish survey of household finances (EFF): Description and methods of the 2002 wave, Documentos Ocasionales. Nr.0409

as a household member with the most accurate knowledge about the household finances. In the Italian Survey, respondents indicated by surveyors as persons primarily responsible of the household budget were coded as decision-makers. Finally, in the Spanish survey, we coded a respondent as decision-maker if he/she was indicated as the person who mostly deals with financial issues or is the owner of the household's accommodation. Individuals coded as decision-makers are the units of observation in our analysis. Females make 36% of units of observation in the Austrian sample, 48% in the Dutch sample, 39% in the Italian sample and 41% in the Spanish sample.

### 3.4.2 Financial Assets

The four national surveys provide the following information about holdings of financial assets. It is known whether a household holds any of the four asset types: bank saving accounts (including short- and long-term savings accounts and house-purchase/building savings accounts), investment funds, directly held bonds and stocks of listed companies. Respondents report also the current market value of each asset they hold. Using this information, we calculate the value of financial wealth by summing the market value of the four asset types.[7] If an individual has a spouse then the spouse's assets are also included in the calculation of financial wealth.

In line with previous literature on household finances, we treat directly held stocks as risky assets.[8] According to the survey data, ownership rates (fraction of individuals in a country who own some stocks) differ significantly among gender groups and countries (see Figure 3.1a). The common pattern shared by all countries is that ownership rate is higher among males than females. However, the magnitude of gender gap varies between countries. The largest gap is observed in Spain – 12 percentage points, followed by Austria with a 10 percent gap, the Netherlands with a 8 points gap and Italy with a 3 percent gap. In all four countries, gender differences in ownership rates are statistically significant. With respect to portfolio share allocated to stocks, the picture changes (Figure 3.1b). In some countries, gender gap is now smaller. Moreover, in Austria and Italy females seem to allocate on average a greater share of their portfolios to stocks. However, the difference is not statistically significant. In Spain both gender groups seem to hold the same relative

[7] We do not include value of other assets like insurance policies or private pension saving plans in our calculation because information about these assets is not known or only partially available. Hence our estimate of financial wealth underestimates the total value of financial assets.

[8] Sunden and Surette, 1998; Jianakoplos and Bernasek, 1998; Bajtelsmit et al., 1999; Bernasek and Shwiff, 2001 measure riskiness of portfolios held in defined contribution plans by looking at the availability and the relative amount of stocks in these portfolios. We extend this approach to the overall holdings of financial assets. By 2004 the majority of financial portfolios held by private households still comprised only of a few asset types with stocks being the riskiest of them. Our data does not allow to identify whether and how many stocks are held indirectly though investment funds. By not considering the indirect ownership of stocks, we underestimate the total stock ownership.

amount of stocks. Only in the Netherlands, females have a smaller share of stocks than males, although the difference is not statistically significant.

### 3.4.3 Socioeconomic and Attitudinal Variables

Using existing studies on determinants of individual financial behavior, we generate a set of individual-specific variables that may affect individual participation and allocation decisions. In addition to the dummy variable $Male$ indicating individuals' gender, this set of variables includes a set of dummy variables $A20$ to $A70$ indicating age group; a dummy variable $Education$ that equals 1 if individual earned a college (or higher) degree and 0 otherwise; a dummy variable $Employed$ equal 1 if individual has a paid job; a dummy variable $Self\ Employed$ indicating whether individual has own business; a continuous variable $Income$ reflecting total annual income of an individual and his/her spouse; a continuous variable $Financial\ Wealth$ (as defined earlier); a dummy variable $Property$ indicating whether an individual owns residential property or not; a dummy variable $Single$ equaling 1 if the individual is single and 0 otherwise. Descriptive statistics of the variables are summarized in Table 3.1

In addition to socioeconomic variables, we also use a set of dummy variables indicating individual attitudes toward financial risks. Importance of controlling for risk preferences when studying gender differences in financial behavior is first highlighted by Sunden and Surette (1998), who use information on individual attitudes toward financial risks collected in the U.S. Survey of Consumer Finances. We use similar measures of risk attitudes obtained in the respective surveys by asking individuals to assess their own willingness to take financial risks. The validity of such measures of risk attitudes is tested in laboratory experiments and it is shown that stated risk attitudes have a strong explanatory power for actual risk taking behavior (see e.g. Dohmen et al. (2006) and Wärneryd (1996)). Moreover, it is shown that stated risk attitudes are correlated with such factors as income, wealth and education. Therefore, information on risk attitudes should be included in the model in order to estimate the biases caused by omitted variables.

The exact formulation of the question about risk attitudes and the scales on which the strength of the willingness to take risks is measured varies among the four national surveys. Table 3.2 documents the exact formulation of questions asked in the national surveys. The Dutch survey applied a 7-point scale, the most detailed, in order to measure the individuals' willingness to take risks in financial matters. The Austrian, Italian and Spanish surveys used a less detailed 4-point scale.[9]

[9]While processing the data, we discovered that the Italian data set is characterized by high non-response rate to the question regarding the willingness to take financial risk: about 65 percent of respondents skipped the question. For our analysis, non-responses mean that all observations with missing data are excluded from the data set, which leads to a significant reduction of the data set. In order to see whether the decision to report risk attitude is influenced by some observed factors, we fit the data to a probit regression model. The

To control for individual attitudes toward financial risks in our regression analysis, we generate a set of dummy-variables indicating how willing an investor is to take financial risks. For Austria and Italy, the set of variables includes four dummy-variables $Risk\,Tolerance\,j$, where $j$ indicates which alternative was selected by a respondent when answering the survey question about risk attitude. For Spain, we also generate a set of four dummy-variables where the dummy variable $Risk\,Tolerance\,1$ equals one if a respondent chose the 4th alternative, $Risk\,Tolerance\,2$ equals one if 3rd alternative was chosen, $Risk\,Tolerance\,3$ equals one if 2nd alternative was chosen and $Risk\,Tolerance\,4$ equals one if the 1st alternative was chosen. The values are assigned in a reverse order to allow higher values to express greater willingness to take risks. Finally, for the Netherlands, we generate a set of 7 dummy-variables $Risk\,Tolerance\,j$, where j=[1,7] with higher values of $j$ corresponding to greater willingness to take risks. Figure 3.2 presents the country-specific distribution of males and females by willingness to take financial risk. In all countries, females clearly outnumber males in the group with lower risk tolerance. Differences are statistically significant at 1%-level. At higher levels of risk tolerance ($Risk\,Tolerance \geq 2$), the proportion of males exceeds the proportion of females, although the differences are not statistically significant.

## 3.5 Results

### 3.5.1 Effects of gender on the probability of holding risky assets

This section reports the test results for the hypothesis that males are more likely to own some risky assets than females, *ceteris paribus*. The hypothesis is tested by estimating the effects of gender on the probability of holding risky assets in a probit regression.[10] Estimation is performed for each country separately. Furthermore, for each country, two specifications of the regression equation are used. The first specification includes all observable socioeconomic variables. The second specification additionally includes a set of dummy variables capturing individual willingness to take financial risks. Estimation results are summarized in Table 3.3. The table reports marginal effects estimated for country-specific means of continuous variables and for base categories of dummy and categorical variables.

dependent variable in this model is an indicator variable equal to 1 if risk attitude is reported and equal to 0 if risk attitude is missing. Explanatory variables include sex, age, income, wealth, employment status, education, family structure and an indicator variable equal to 1 if risky assets are owned and equal to 0 otherwise. Our results show that probability of non-response is negatively related to income, wealth, holdings of risky financial assets, and is smaller for those who are employed as compared to unemployed. Thus, the sub-set of individuals who provide information on their risk attitudes over-samples the wealthy and those with ownership of risky assets. This should be kept in mind when analyzing the influence of risk attitudes on investment decisions.

[10] We also estimate the equation using a logit regression model. The log-likelihood for the probit model is however higher than for the logit model in all five countries, favoring the probit model.

The Obtained $R^2$ indicate that explanatory variables included in the regression equation explain a considerable amount of variation in the outcome variable. Moreover, inclusion of dummy-variables capturing risk attitudes further increases the $R^2$, hence improving the explanatory power. In line with our expectations, wealth and risk attitudes seem to play a decisive role in the decision to hold risky assets. The effect of these covariates is similar in all four countries: the probability of holding risky assets increases significantly with wealth and individual willingness to take financial risks. Educational level is also found to increase the likelihood of ownership in all countries. However, in the Netherlands the effect is not statistically significant. Effects of the other explanatory variables differ across countries. For instance, we find that probability of holding risky assets decreases with age in Austria, but barely changes with age in the other countries. Dissimilarities between country-specific effect are reported in previous studies and are driven by country-specific factors that are not taken into account in the analysis.[11]

Looking at the results obtained for the first specification, the coefficients on the main variable of interest *Male* are positive and statistically significant in all four countries. *Ceteris paribus*, males are, by about 4 percentage points, more likely to invest in risky assets than females in Austria, by 8 percent in the Netherlands, by 9 percent in Italy and by 2 percent in Spain. These results are consistent with the common belief that females are more risk averse than males and, in that sense, do not present any novel evidence. Yet, the results obtained in for the second specification deserve additional consideration.

The second specification additionally includes indicators of individual willingness to take financial risks. The estimation results show that controlling for risk attitudes renders coefficients statistically insignificant in Austria, the Netherlands and Spain. This result suggests that the observed disparities in the actual risk taking between males and females stem from the differences in the gender-specific distributions of risk preferences in the population (see Figure 3.2). Thus, males and females in the three countries seem to make investment decisions in accord with their individual risk preferences. A different picture emerges in Italy. Here the effect of gender remains significant, even after we control for individual risk preferences: males are, by almost 8 percent, more likely to hold risky assets than females, holding stated risk preferences constant. It seems that females tend to participate in the market for risky assets less frequently than expected given their risk preferences. Or, equivalently, males tend to acquire risky assets, even though their risk aversion is very high. All in all, this result indicates that, in Italy – the country with the lowest gender equality of those studied – gender differences in acquisition of risky financial are driven by two factors: gender differences in individual risk preferences and gender-based differences in social roles. Social inequality magnifies the effect of gender differences in risk preferences. In contrast, in Austria, the Netherlands and Spain – the countries with relatively high gen-

[11] For instance, Guiso et al. (2003) name differences in the national capital gain taxation systems as one of important determinants of cross-country variation in portfolio decisions.

der equality – gender differences in ownership of risky assets can be viewed as a result of one factor – the gender differences in risk preferences. Hence, in both cases gender conveys useful information about the propensity for risk taking and can serve as a predictor of the probability of acquisition of risky assets. However, for societies with relatively high gender equality, individual risk preference is a much better predictor of risk taking because it conveys more accurate information than gender.

### 3.5.2 Effects of gender on the share of wealth allocated to risky assets

Let us now look at the test results for the hypothesis that, conditional on owning some risky assets, men invest a higher share of their financial wealth into these assets than females. The effect of explanatory variables on the share of risky assets is estimated using the Heckman two-stage estimation procedure. As previously done, we estimate two specifications of the regression equation for each country: the first one includes only socioeconomic and demographic information, and the second one includes individual risk preferences. The first-stage equation corresponds to that used in the analysis of the ownership decision (see Table 3.3). The second-stage equation essentially includes the same explanatory variable as the first-stage equation with two adjustments: wealth enters the second-stage equation as a set of dummies indicating the 1st, 2nd, 3rd and 4th quartiles of the sample distribution; and the dummy variable *Property* is excluded from the equation. This adjustment is necessarily in order to enable identification of the model. Coefficient estimates obtained for the second-stage regression are reported in Table 3.4.

Overall, we find that most of the included observable characteristics have little effect on the allocation decision. Although wealth is found to have some positive effect on the share of risky assets in the Netherlands and Italy, it does not for Austria and Spain. Furthermore, individual willingness to take risks is positively related to the share of risky assets only in Italy and Austria. Hence, conditional on ownership of risky assets, the decision about what portion of wealth to invest in these assets is driven by unobserved individual-specific effects rather than by the observed socioeconomic characteristics.

According to the model specification where risk preferences are not taken into account, gender has no statistically significant effect on the portfolio share of risky assets in all countries except Italy. *Ceteris paribus*, males in Italy will invest 9 precent more in risky assets than females. When risk preferences are taken into account, gender effects in Austria, the Netherlands and Spain remain insignificant and also become insignificant in Italy. Hence, our analysis suggests that, in Austria, the Netherlands and Spain, there are no differences between males and females with respect to risk-taking in the portfolio allocation decisions. In contrast, the Italian data provide evidence of significant gender differences in the risk-taking.

It should be noted that results reported in Table 3.4 also show that parameter $\lambda$ representing the effect of the correction term Mills-Ratio is only statistically significant for Italy. Thus, we find no evidence of correlation between the two stages of the portfolio decision through unobservable factors in Austria, the Netherlands and Spain. In this case, a two-stage estimation procedure is not required. To test the robustness of our results with respect to the choice of the estimation procedure, we also estimate the effect of gender on the portfolio share of risky assets using Tobit estimation procedure.[12] The results confirm the previous finding: gender does not significantly influence the allocation decision.

### 3.5.3 Discussion and Limitations

Results of our analysis suggest that gender differences in financial risk taking vary across countries and across the types of financial decisions. We interpret the first finding as evidence of the importance of cultural factors in financial behavior of males and females. We agree that this evidence relies on a very small sample of countries and thus a casual effect cannot be proved. Moreover, we cannot completely rule out that the result is driven by data-related issues rather than by differences in cultural factors. We make all possible effort to minimize the effect of data-related problems by selecting very similar surveys and applying the same estimation methodology to all considered countries. Nevertheless, a comprehensive test of casual relationship between cultural factors and risk-taking behavior of males and females requires high-quality data for a wider set of countries.

Our second main finding is that females are less likely to engage in risky activities, however, conditional on engaging in such activities take equal risks as males. On the one hand, this finding differs from the evidence provided by Bajtelsmit et al. (1999) and Jianakoplos and Bernasek (1998) who find significant differences in the structure of portfolios between males and females holding some risky assets. The discrepancy in the evidence may be due to the specifics of the data used in these studies. For instance, inference of Jianakoplos and Bernasek (1998) relies on the risk-taking behavior of single females only. Yet, for obvious reasons, behavior of single females is not representative of the behavior of all females.[13] Bajtelsmit et al. (1999) analyze risk-taking in the defined contribution pension plans rather than in the entire financial portfolios and therefore their results are not directly comparable to our analysis. On the other hand, our results are by and large in line with literature that studies risk-taking behavior of males and females in specific sub-populations, for example, among investment fund managers (Johnson and Powell, 1994) or entrepreneurs (Caliendo and Kritikos, 2008). The main finding of this literature is that males and females who vol-

[12] Results from the Tobit estimation are available from the authors upon request.

[13] Even taking into account that married females generally own less wealth than their husbands (Sierminska et al. (2010)), and hence are on average not much wealthier than single females, a singe female might behave more risk-averse than an equally wealthy married female because the latter has an additional background safety in form of husband's income and assets.

untarily engage in a risk taking activity have similar propensity for risk taking. What we observe in the household data may reflect a similar selection of individuals whereby males and female who decide to acquire risky assets do not differ significantly with respect to risk preferences. However, this finding holds only in countries with relatively high gender equality in social roles and opportunities.

## 3.6 Conclusions

This study investigates the question whether gender can be considered as a good predictor of the propensity for risk taking in two types of portfolio decisions – the ownership and the allocation decision. Using the national surveys of household finances in four European countries, we show that extent of risk taking by males and females depends on the type of financial decision and on the degree of gender equality in a society. While females are found to be less willing to take financial risks than males in all four considered countries, the discrepancy in actual risk taking is most pronounced in Italy – the country with the greatest gender inequality compared to the other three countries. In particular, we find that in Italy females are less likely to hold risky assets than males, even if they report equal willingness to take risks. In contrast, in Austria, the Netherlands and Spain males and females with equal risk preferences are equally likely to hold risky financial assets in their portfolios.

Furthermore, we find that in countries with relatively low gender inequality, gender does not play a role in the decision about what portfolio share is allocated to risky assets, once individuals decide to acquire such assets. Therefore, males and females who voluntarily engage in risky investments are equally prone to take risks. Hence, the popular belief that females are less risk prone does not hold in this instance. A special case is Italy: Here, females are found to allocate smaller portfolio shares to risky assets than males, given that they own some risky assets.

To sum up, individuals' gender cannot always serve as a good predictor of the propensity to take financial risks. In particular, gender can serve as a good predictor only with respect to acquisition of risky financial assets. However, in societies with relatively high gender equality, individual risk preferences convey more accurate information about the propensity for risk taking than gender and, therefore, are a much better predictor. Moreover, gender seems to have no predictive power at all with respect to the portfolio share of risky assets in countries with relatively high gender equality.

These findings have important implications for scholars and practitioners. In particular, the results of the study speak against a simplistic approach of using an individuals' gender as a proxy for risk aversion. Our findings also show that financial advice should be provided in accordance with individual risk preferences rather than based on the stereotypical believes about a "typical" man or woman. Furthermore, the findings imply that not only gender and stated risk preferences of individuals should be taken into account, but also their cultural background.

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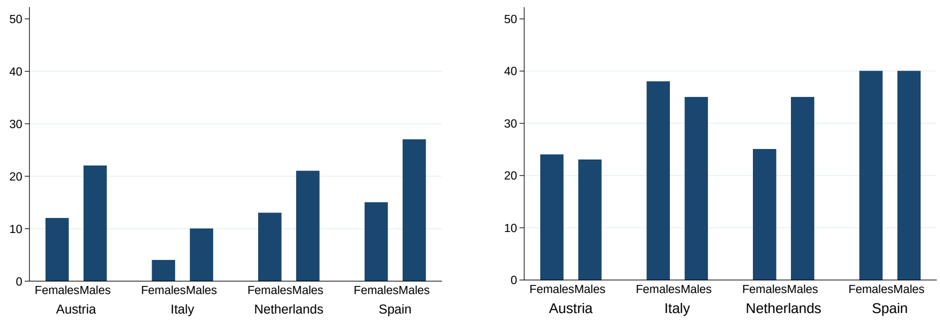
# Appendix A

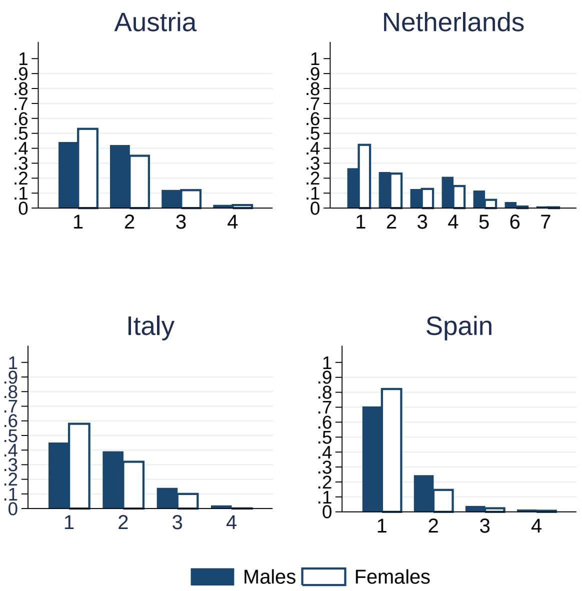
Figure 3.1: Ownership rates and portfolio shares of stocks




a) Onership rate

b) Average portfolio share

Figure 3.2: Distribution of individuals by the stated willingness to take financial risks




*Note*: Each histogram shows country-specific distributions of males and females by the stated willingness to take financial risks. The strength of the willingness is measured on an ordinal scale with higher numbers corresponding to higher willingness to take risks.

Table 3.1: Descriptive statistics by gender

| | Austria | | Netherlands | | Italy | | Spain | |
|---|---|---|---|---|---|---|---|---|
| | Females | Males | Females | Males | Females | Males | Females | Males |
| Income, in Euro | 25,256 | 33,966 | 25,605 | 31,165 | 19,838 | 27,346 | 23,312 | 35,797 |
| | (13,024) | (13,680) | (21,712) | (26,717) | (15,873) | (28,211) | (32,066) | (50,268) |
| Financial Wealth, in Euro | 29,576 | 56,866 | 9,889 | 23,602 | 15,728 | 25,404 | 31,755 | 64,411 |
| | (53,172) | (120,099) | (24,813) | (70,186) | (55,712) | (72,627) | (88,371) | (135,367) |
| Real Property | 0.53 | 0.65 | 0.70 | 0.71 | 0.67 | 0.72 | 0.41 | 0.65 |
| | (0.50) | (0.48) | (0.46) | (0.45) | (0.47) | (0.45) | (0.49) | (0.48) |
| Self-Employed | 0.05 | 0.08 | 0.03 | 0.05 | 0.05 | 0.14 | 0.06 | 0.18 |
| | (0.23) | (0.27) | (0.17) | (0.21) | (0.22) | (0.35) | (0.23) | (0.38) |
| Education | 0.43 | 0.39 | 0.23 | 0.24 | 0.32 | 0.41 | 0.20 | 0.29 |
| | (0.50) | (0.49) | (0.42) | (0.42) | (0.47) | (0.49) | (0.40) | (0.45) |
| Age $\leq$ 30 | 0.08 | 0.05 | 0.08 | 0.04 | 0.04 | 0.03 | 0.05 | 0.03 |
| | (0.27) | (0.22) | (0.26) | (0.20) | (0.19) | (0.17) | (0.22) | (0.18) |
| Age 30-39 | 0.20 | 0.14 | 0.24 | 0.19 | 0.13 | 0.13 | 0.14 | 0.11 |
| | (0.40) | (0.35) | (0.43) | (0.39) | (0.34) | (0.33) | (0.35) | (0.31) |
| Age 40-49 | 0.21 | 0.25 | 0.25 | 0.23 | 0.18 | 0.19 | 0.20 | 0.17 |
| | (0.40) | (0.43) | (0.43) | (0.42) | (0.39) | (0.39) | (0.40) | (0.38) |
| Age 50-59 | 0.18 | 0.19 | 0.22 | 0.23 | 0.18 | 0.24 | 0.17 | 0.20 |
| | (0.38) | (0.40) | (0.41) | (0.42) | (0.38) | (0.42) | (0.38) | (0.40) |
| Age 60-69 | 0.20 | 0.24 | 0.14 | 0.17 | 0.16 | 0.21 | 0.18 | 0.24 |
| | (0.40) | (0.43) | (0.34) | (0.37) | (0.37) | (0.41) | (0.38) | (0.43) |
| Age $\geq$70 | 0.13 | 0.12 | 0.08 | 0.15 | 0.31 | 0.21 | 0.26 | 0.25 |
| | (0.34) | (0.32) | (0.27) | (0.35) | (0.46) | (0.41) | (0.44) | (0.44) |
| Single | 0.69 | 0.21 | 0.36 | 0.30 | 0.62 | 0.19 | 0.49 | 0.19 |
| | (0.46) | (0.41) | (0.48) | (0.46) | (0.49) | (0.40) | (0.50) | (0.39) |
| Children | 0.40 | 0.50 | 0.83 | 0.72 | 0.32 | 0.41 | 0.77 | 0.79 |
| | (0.84) | (0.92) | (1.11) | (1.11) | (0.70) | (0.77) | (0.94) | (0.95) |

Note: The table reports country-specific sample means and standard deviations (in parentheses); variable *Financial Wealth* is winsorized to 99%.

Table 3.2: Survey questions about the attitude toward financial risks

| **Country** | **Survey question** |
|---|---|
| Austria | "*For savings I prefer secure investment instruments and avoid risk*"<br>1=completely applicable;<br>2=rather applicable;<br>3=rather not applicable;<br>4=completely inapplicable. |
| Netherlands | *Please indicate on a scale from 1 to 7 to what extent you agree with the "I am prepared to take the risk to lose money, when there is also a chance to gain money", where 1 indicates 'totally disagree' and 7 indicates 'totally agree'.* |
| Spain | "*Which of the following statements do you feel best describes your household in terms of the amount of financial risk you are willing to run when you make an investment?*"<br>1=Take on a lot of risk in the expectation of obtaining a lot of profit;<br>2=Take on a reasonable amount of risk in the expectation of obtaining an above-normal profit;<br>3=Take on a medium level of risk in the expectation of obtaining an average profit;<br>4=You are not willing to take on financial risk. |
| Italy | "*Which of the statements on this page comes closest to the amount of financial risk that you are willing to take when you save or make investments?*"<br>1=low returns, without any risk of losing your capital;<br>2=a reasonable return, with a good degree of security for your invested capital;<br>3=a good return, with reasonable security for your invested capital;<br>4=very high returns, regardless of a high risk of losing part of your capital. |

## Table 3.3: Effect of Gender on the Probability of Owning Risky Assets

This table shows results from estimating the likelihood of holding risky assets using a probit regression model. The dependent variable is a binary variable equal to 1 if some *risky financial assets* are held and 0 otherwise. Columns denoted as (1) report estimation results for the basic specification of equation (1). Columns denoted as (2) extend the specification by including variables capturing attitudes toward risk taking. Reported are marginal effects of the explanatory variables and robust standard errors in parentheses. Marginal effects are estimated at country-specific mean values of explanatory variables. *, ** and *** correspond to 10%, 5% and 1% significance levels respectively.

| | Austria | | Netherlands | | Italy | | Spain | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Male | 0.039*** | 0.021 | 0.085*** | 0.044 | 0.087*** | 0.075*** | 0.020* | 0.011 |
| | (0.014) | (0.015) | (0.027) | (0.031) | (0.016) | (0.016) | (0.010) | (0.010) |
| ln(Income) | 0.095*** | 0.080*** | -0.002 | -0.007 | 0.117*** | 0.102*** | 0.007*** | 0.005** |
| | (0.018) | (0.018) | (0.003) | (0.005) | (0.016) | (0.015) | (0.002) | (0.002) |
| II wealth quartile | 0.129*** | 0.156*** | -0.006 | -0.043 | 0.191 | 0.268** | 0.155*** | 0.159*** |
| | (0.037) | (0.04) | (0.034) | (0.046) | (0.145) | (0.135) | (0.031) | (0.032) |
| III wealth quartile | 0.258*** | 0.286*** | 0.107*** | 0.138*** | 0.262** | 0.298*** | 0.424*** | 0.415*** |
| | (0.04) | (0.043) | (0.035) | (0.043) | (0.13) | (0.115) | (0.032) | (0.033) |
| IV wealth quartile | 0.524*** | 0.526*** | 0.234*** | 0.309*** | 0.286*** | 0.292*** | 0.665*** | 0.622*** |
| | (0.042) | (0.044) | (0.041) | (0.045) | (0.084) | (0.071) | (0.025) | (0.028) |
| Real Property | 0.042*** | 0.040*** | 0.061*** | 0.057** | 0.023 | 0.013 | -0.016 | -0.008 |
| | (0.013) | (0.012) | (0.021) | (0.027) | (0.019) | (0.019) | (0.013) | (0.013) |
| Self-Employed | -0.001 | -0.017 | 0.034 | -0.032 | -0.013 | -0.021 | 0.038*** | 0.017 |
| | (0.024) | (0.021) | (0.055) | (0.069) | (0.022) | (0.021) | (0.015) | (0.014) |
| Education | 0.049*** | 0.047*** | 0.034 | 0.020 | 0.109*** | 0.082*** | 0.106*** | 0.080*** |
| | (0.014) | (0.014) | (0.023) | (0.030) | (0.026) | (0.025) | (0.013) | (0.012) |
| Age 30-39 | -0.055** | -0.04 | 0.070 | 0.124 | 0.202* | 0.133 | -0.023 | -0.026 |
| | (0.023) | (0.024) | (0.070) | (0.093) | (0.104) | (0.100) | (0.034) | (0.033) |
| Age 40-49 | -0.095*** | -0.075*** | 0.047 | 0.112 | 0.191* | 0.136 | -0.000 | -0.005 |
| | (0.020) | (0.021) | (0.066) | (0.091) | (0.098) | (0.096) | (0.036) | (0.036) |
| Age 50-59 | -0.107*** | -0.081*** | 0.042 | 0.126 | 0.156* | 0.114 | 0.041 | 0.043 |
| | (0.017) | (0.019) | (0.063) | (0.088) | (0.092) | (0.09) | (0.041) | (0.041) |
| Age 60-69 | -0.109*** | -0.078*** | 0.009 | 0.086 | 0.158 | 0.113 | 0.052 | 0.064* |
| | (0.021) | (0.024) | (0.060) | (0.091) | (0.097) | (0.095) | (0.041) | (0.042) |
| Age 70-79 | -0.123*** | -0.099*** | 0.041 | 0.122 | 0.128 | 0.100 | 0.053 | 0.084** |
| | (0.013) | (0.015) | (0.068) | (0.098) | (0.094) | (0.093) | (0.040) | (0.043) |
| Single | 0.045** | 0.033* | 0.016 | 0.007 | 0.023 | 0.027 | -0.038** | -0.030** |
| | (0.02) | (0.019) | (0.022) | (0.031) | (0.02) | (0.02) | (0.015) | (0.015) |
| Children | -0.007 | -0.005 | 0.019* | 0.027* | 0.019 | 0.019 | 0.007 | 0.007 |
| | (0.008) | (0.008) | (0.011) | (0.014) | (0.012) | (0.012) | (0.006) | (0.006) |
| Risk Tolerance 2 | | 0.077*** | | 0.044 | | 0.114*** | | 0.190*** |
| | | (0.012) | | (0.028) | | (0.016) | | (0.016) |
| Risk Tolerance 3 | | 0.222*** | | 0.090** | | 0.240*** | | 0.212*** |
| | | (0.031) | | (0.042) | | (0.027) | | (0.034) |
| Risk Tolerance 4 | | 0.229*** | | 0.177*** | | 0.509*** | | 0.131*** |
| | | (0.062) | | (0.037) | | (0.109) | | (0.052) |
| Risk Tolerance 5 | | | | 0.249*** | | | | |
| | | | | (0.048) | | | | |
| Risk Tolerance 6 | | | | 0.468*** | | | | |
| | | | | (0.103) | | | | |
| Risk Tolerance 7 | | | | 0.303*** | | | | |
| | | | | (0.144) | | | | |
| Pseudo-$R^2$ | 0.26 | 0.30 | 0.10 | 0.17 | 0.13 | 0.17 | 0.32 | 0.36 |
| Number of obs. | 2,556 | 2,556 | 1,091 | 985 | 2,806 | 2,806 | 5,833 | 5,833 |

## Table 3.4: Effect of Gender on the Portfolio Share of Risky Assets

This table summarizes the results of estimation of equation (2) by means of the Heckman two-step procedure. The dependent variable is the portfolio share invested in *risky financial assets*. The first stage selection equation (not reported) corresponds to equation (1). Columns denoted as (1) report estimation results for the basic specification of the first and the second-stage equation. Columns denoted as (2) extend both equations by including variables capturing attitudes toward risk taking. *, ** and *** correspond to 10%, 5% and 1% significance levels respectively.

| | Austria | | Netherlands | | Italy | | Spain | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Male | 0.001 | -0.009 | 0.098 | 0.049 | 0.093** | 0.078 | -0.007 | -0.018 |
| | (0.020) | (0.020) | (0.064) | (0.059) | (0.046) | (0.048) | (0.022) | (0.022) |
| ln(Income) | 0.037 | 0.032 | 0.021** | 0.017* | 0.108** | 0.098** | 0.004 | -0.003 |
| | (0.029) | (0.028) | (0.009) | (0.009) | (0.047) | (0.050) | (0.008) | (0.008) |
| ln(Financial wealth) | -0.004 | -0.009 | -0.013* | -0.014** | -0.012 | -0.020 | -0.002 | -0.003 |
| | (0.012) | (0.012) | (0.007) | (0.007) | (0.016) | (0.016) | (0.005) | (0.004) |
| Self-Employed | -0.008 | -0.007 | 0.010 | 0.019 | 0.089* | 0.069 | 0.070 | 0.063 |
| | (0.017) | (0.017) | (0.043) | (0.041) | (0.046) | (0.046) | (0.021) | (0.020) |
| Education | 0.018 | 0.017 | -0.074 | -0.150 | 0.198 | 0.116 | -0.077 | -0.078 |
| | (0.041) | (0.041) | (0.139) | (0.151) | (0.161) | (0.158) | (0.085) | (0.084) |
| Age 30-39 | -0.008 | -0.004 | -0.026 | -0.121 | 0.203 | 0.127 | -0.032 | -0.036 |
| | (0.040) | (0.039) | (0.139) | (0.152) | (0.160) | (0.158) | (0.082) | (0.081) |
| Age 40-49 | -0.030 | -0.022 | -0.047 | -0.110 | 0.166 | 0.099 | 0.069 | 0.071 |
| | (0.042) | (0.041) | (0.137) | (0.152) | (0.157) | (0.155) | (0.081) | (0.081) |
| Age 50-59 | -0.003 | 0.011 | -0.032 | -0.131 | 0.283* | 0.211 | 0.052 | 0.055 |
| | (0.048) | (0.047) | (0.146) | (0.160) | (0.162) | (0.160) | (0.082) | (0.082) |
| Age 60-69 | -0.022 | -0.002 | -0.108 | -0.154 | 0.168 | 0.123 | 0.100 | 0.112 |
| | (0.059) | (0.057) | (0.158) | (0.171) | (0.161) | (0.159) | (0.084) | (0.084) |
| Age $\geq$ 70 | 0.006 | 0.001 | -0.081 | -0.145 | 0.013 | -0.014 | 0.030 | 0.026 |
| | (0.030) | (0.030) | (0.095) | (0.109) | (0.040) | (0.042) | (0.024) | (0.024) |
| Single | 0.051** | 0.045* | -0.014 | -0.033 | 0.029 | 0.038 | -0.023 | -0.026 |
| | (0.023) | (0.023) | (0.049) | (0.048) | (0.036) | (0.038) | (0.024) | (0.024) |
| Children | -0.012 | -0.010 | 0.007 | 0.012 | 0.041* | 0.040* | -0.001 | 0.001 |
| | (0.011) | (0.011) | (0.023) | (0.023) | (0.022) | (0.023) | (0.011) | (0.011) |
| Risk Tolerance 2 | | 0.031 | | 0.051 | | 0.200*** | | 0.069 |
| | | (0.024) | | (0.071) | | (0.065) | | (0.027) |
| Risk Tolerance 3 | | 0.056* | | -0.035 | | 0.379*** | | 0.167 |
| | | (0.033) | | (0.084) | | (0.100) | | (0.039) |
| Risk Tolerance 4 | | 0.137*** | | 0.073 | | 0.749*** | | 0.181 |
| | | (0.048) | | (0.082) | | (0.172) | | (0.065) |
| Risk Tolerance 5 | | | | 0.105 | | | | |
| | | | | (0.100) | | | | |
| Risk Tolerance 6 | | | | 0.005 | | | | |
| | | | | (0.142) | | | | |
| Risk Tolerance 7 | | | | -0.087 | | | | |
| | | | | (0.175) | | | | |
| Constant | -0.162 | -0.098 | 0.090 | 0.232 | -1.463* | -1.410 | 0.257 | 0.308 |
| | (0.375) | (0.371) | (0.299) | (0.325) | (0.794) | (0.884) | (0.170) | (0.172) |
| $\lambda$ | 0.036 | 0.037 | -0.013 | -0.025 | 0.428*** | 0.446*** | 0.062 | 0.064 |
| | (0.034) | (0.035) | (0.097) | (0.096) | (0.116) | (0.140) | (0.037) | (0.039) |
| Total number of obs. | 2,556 | 2,556 | 1,091 | 985 | 2,806 | 2,806 | 5,833 | 5,833 |
| Number of uncensored obs. | 463 | 463 | 229 | 212 | 592 | 592 | 1,343 | 1,343 |

# Chapter 4

# Does Gender Affect the Risk Propensity of Retail Investors? Evidence from Peer-to-Peer Lending

***Abstract***: This study investigates the role of gender in financial risk-taking. Specifically, I ask whether female investors tend to fund less risky investment projects than males. To answer this question, I use real-life investment data collected at the largest German market for peer-to-peer lending. Investors' utility is assumed to be a function of the projects expected return and its standard deviation, whereas standard deviation serves as a measure of risk. Gender differences regarding the responses to projects' risk are tested by estimating a random parameter regression model that allows for variation of risk preferences across investors. Estimation results provide *no* evidence of gender differences in investors' risk propensity: On average, male and female investors respond similarly to projects' risk. Moreover, no differences between male and female investors are found with respect to other characteristics of projects that may serve as a proxy for projects' riskiness. Significant gender differences in investors' tastes are found only with respect to preferred investment duration, purpose of investment project and borrowers' age.

***JEL***: G11, G21, J16
***Keywords***: gender, retail investors, risk propensity

## 4.1 Introduction

The financial crisis of the early 21st Century triggered, among many other things, a heated public debate about the role of gender in the financial behavior of individuals.[1] One conjecture voiced in the debate is that excessive risk-taking in the financial markets is to be

[1] See e.g. Economist (2009), Bennhold (2009) and Oakeshott (2009)

blamed on the prevalence of males in the decision-making positions in the financial industry. As Neelie Kroes, the EU competition commissioner, put it: *"... the collapse of Lehman Brothers would never have happened if there'd been Lehman Sisters with them."*[2] Such claims rely primarily on the popular gender stereotype that males seek greater risk and are overconfident in financial matters than females. An important question is whether gender stereotype reflects the true state of things. Does gender really affect the risk-taking propensity? Literature investigating this question is extensive, however, no conclusive answer has been provided. So far, most evidence is based on household surveys or laboratory experiments. In contrast, direct evidence on real-life investment behavior is scarce and essentially limited to studies of professional investors.

This study contributes to the literature by examining financial behavior of males and females using real-life data. The aim of the study is to test gender differences in the propensity for risk taking by retail investors who participate in a new segment of financial markets known as *peer-to-peer (p2p)* lending. Peer-to-peer lending means direct lending and borrowing between individuals ("peers") without intermediation of a traditional financial institution like a bank. The data are collected from the largest German p2p marketplace *Smava.de*. In this marketplace, individuals lend funds for a variety of purposes ranging from large consumer expenditures to small business investments. The loans are neither collateralized nor guaranteed and lenders can incur losses if borrowers default. Hence, p2p-lenders can be seen as investors who fund risky projects.

Relying on the $\mu$-$\sigma$ approach, I assume that utility attached by investors to a risky project depends on the project's expected return $\mu$ and its standard deviation $\sigma$. The more risk averse an investor is, the more his/her utility decreases in response to a small increase in $\sigma$. This relationship serves as a basis for the test of gender differences in risk propensity. The aim of the test is to answer the question: *Are female investors participating in the German p2p-lending more risk-averse than male investors?* If female investors indeed exhibit higher risk aversion than male investors, their utility will decrease more than the utility of males in response to a marginal increase in $\sigma$, *ceteris paribus*. Inference about the effect of $\sigma$ on utility is derived from investors' actual choices.

Advantages of using the p2p-lending data for the analysis are threefold. Firstly, all participating investors are exposed to the same market-related factors: there is only one type of financial product, same investment rules apply for every one and all participants have access to the same information. Therefore, it can be argued that differences in the observed investment choices stem exclusively from investor-related factors. Secondly, a complete history of investment choices of each participant including the characteristics of the investment alternatives is observable. Thirdly, investors' gender is observable to

[2] Indeed, all members of the executive management at *Lehman Brothers* at the time of the collapse were male. The bank is not an exception: The three German banks – Deutsche Bank, Kommerzbank and HypoVereinsbank – have all-male executive management teams.

researcher. All these features make p2p data well suited for a study of gender effects on the propensity for risk-taking of retail investors.

Estimation of investors' responses to the riskiness of investment projects relies on mixed logit regression – a qualitative choice model that accommodates repeated choice data. Repeated choice arises because during the observation period majority of investors conducted more than one investment. This advantageous feature of the data eliminates problems stemming from the fact that not all investor-specific factors are observable to researcher.

Results of regression analysis provide *no* evidence of gender differences in investors' risk propensity: On average, male and female investors respond similarly to changes in projects mean-variance profile. Moreover, no differences between male and female investors are found with respect to other characteristics of investment projects that may serve as proxy for projects' riskiness. Significant gender differences in investor taste are found only with respect to preferred investment duration, purpose of investment project and borrower age.

The remainder of the paper is organized as follows. In Section 4.2, I review studies examining the role of gender in individuals' propensity for risk taking in financial decisions. Information about p2p-credit markets and lending mechanism at *Smava.de* is provided in Section 4.3. In Section 4.4, I formulate the research hypothesis. Section 4.5 is devoted to empirical analysis. Here, I firstly describe the econometric model and the data employed to test the research hypothesis. Then, I report and discuss the main estimation results. The last section concludes.

## 4.2 Literature Review

Academic research on the role of gender in the financial behavior of individuals has a long history. Nonetheless, the question regarding the effect of gender on the propensity for risk-taking remains unanswered.

A large group of studies, especially those that analyze financial behavior of individuals in the population at large, suggest that females are on average more risk averse than males, *ceteris paribus* (Jianakoplos and Bernasek, 1998; Sunden and Surette, 1998; Bernasek and Shwiff, 2001). However, these studies rely on household survey data providing only general information about investments, while such important parameters as expected return, risk or transaction costs are not known. Hence, the level of risk taken by an individual investor cannot be measured exactly. Moreover, in the most survey-based data, financial assets are aggregated at household level making it difficult to identify who is actually responsible for an investment decision in a multi-person household.

A few empirical studies try to overcome these limitations by focusing on professionally trained investors, mostly managers of investment funds, who take risky financial decisions in the course of their jobs. Intuition suggests that males and females who deliberately and actively engage in risky financial activity and have the same professional training should, on average, exhibit similar risk propensity. This should hold even when in population at large females are found to be less risk tolerant than males. Nonetheless, studies of behavior of professional investors provide mixed evidence. Johnson and Powell (1994) and Atkinson et al. (2003) find no differences in the behavior of male and female managers. In contrast, Olsen and Cox (2001), Beckmann and Menkhoff (2008) and Niessen and Ruenzi (2007) show that female managers follow less risky investment styles than their male counterparts. Noteworthy, the latter group of studies has one methodological feature in common. The studied funds are very heterogenous ranging from pure bond-funds to pure equity-funds so that the sampled individuals work in very different settings and face different investment tasks. This may preclude unbiased evidence on individual-specific factors of investment decisions.

So far, a careful control over the factors related to investment task could only be assured in laboratory experiments. A number of experimental studies investigate gender differences in risk preferences in objective probability lotteries with both real and hypothetical outcomes (Powell and Ansic, 1997; Schubert et al., 1999; Holt and Laury, 2002; Dohmen et al., 2005; Fehr-Duda and Schubert, 2006; Eckel and Grossman, 2008).[3] Although a majority of the studies confirm the gender stereotype, there are some notable exceptions. For instance, Schubert et al. (1999) find that risk propensity of males and females depends strongly on whether experiments involve abstract gambles or contextually framed lotteries. In the latter setting females and males do not exhibit significant differences in risk propensity. Interesting evidence is provided by Holt and Laury (2002) who show that the effect of gender varies with the level of payoff. Females behave more risk averse than males when lotteries involve low payoffs. However, when lotteries involve high payoffs, no differences between males and females are documented. Thus, experimental evidence on gender differences should be enjoyed carefully as gender differences in financial behavior seems to be sensitive to contextual framing and to the level of payoffs.

This study contributes to the existing literature in several important ways. First, it complements experimental evidence by resolving the concerns regarding the consistency of behavior in a laboratory with behavior in real life. Furthermore, unlike most studies based on observational data, the study analyzes risk-taking in a situation where all investors make decisions about the same type of investment product. Finally, the study provides rare evidence on the behavior of retail investors with detailed information about investments' characteristics available.

[3] A concise overview of these studies is provided by Croson and Gneezy (2009).

## 4.3 German Market for Peer-to-Peer Lending *Smava*

### 4.3.1 What is Peer-to-Peer Lending?

The term "peer-to-peer lending" refers to direct lending between private persons without intermediation of traditional financial institutions like banks. Classical examples of p2p loans are loans granted among friends or family members. The novelty of the modern p2p lending is the emergence of internet-based marketplaces (so called "platforms") where funds are transferred from surplus and deficit agents and the agents do not know each other personally. The surplus agents, i.e. lenders, provide funds with interest. The deficit agents, i.e. borrowers, are contractually bound to repay the principal and the interest. They can, however, default on their debt obligations and inflict losses on lenders.

The first p2p platform, *Zopa*, was founded in 2005 in the UK. Since then, more than 30 independent market places started in the USA and continental Europe. Currently, the total amount of p2p loans originated by the largest platforms in the USA and Europe – Prosper, Lending Club, Zopa, Smava and Auxmoney – amounts to €600 million.[4] Compared to the volume of the traditional consumer credit market, peer-to-peer lending is still a niche product. Nevertheless, its phenomenon attracts significant attention of general public, financial industry professionals and academics.[5]

### 4.3.2 How does *Smava* function?

This study focuses on the largest German p2p platform *Smava.de*. The platform was launched in March 2007. By the end of March 2010, a total of 4,148 loan applications were posted on the platform. This leads to a total volume of ca. € 25 million, the result of 3,354 signed loan contracts (Figure 5.1)[6] The average amount of loan is approximately € 8 thousand.

The market functions in the following way. Individuals who want to invest or borrow on the platform must register and prove their identity. Investing is allowed to private individuals who are at least 18 years old and are residents of Germany. Borrowing is allowed to private persons who comply with a range of requirements. First, applicants must be at least 18 years old and have a monthly income of at least € 1,000. Secondly, only those whose individual financial burden does not exceed 67 % are eligible to borrow at the platform. Financial burden is measured as a ratio of monthly payments on all outstanding consumer debts (including loans taken at *Smava*) to the borrower's personal monthly disposable income. Mortgage payments are treated as expenditures and subtracted from the disposable

[4]Own calculations of the author based on official reports of the four platforms.

[5]For the general information see e.g. FTD (2009), Sviokla (2009) and Kim (2009); on financial industry analysis see Meyer (2009); and on academic research see Pope and Sydnor (2008), Freedman and Jin (2008), Garman et al. (2008) and Duarte et al. (2009).

[6]Own calculations of the author.

income. Income by other household members, as well as household savings, are not taken into account. Depending on the obtained ratio, borrowers are rated on a scale from 1 to 4 and assigned the so called KDF-indicator as described in Table 5.3. Finally, the platform accepts only applicants with credit scores ranging from A to H. This rating, commonly referred to as a "Schufa-rating", is assigned to individuals by Schufa, the German national credit bureau, and measures individual's creditworthiness on a 12-point scale from A (the best) to M (the worst). Each rating score corresponds to an estimate of the probability that a borrower defaults on his obligations (see Table 5.2). Applicants' identity is verified via *postident* procedure, a procedure through which individuals prove their identity through verification procedures carried out by employees of Deutsche Post at their local post office. The verified identity is not revealed to other market participants; instead both investors and borrowers operate at the platform under usernames.

After successful registration, borrowers post loan applications on the platform's web page. A loan application specifies the amount of money the applicant wants to borrow, for how long and what nominal annual interest rate he or she is willing to pay. Two restrictions are imposed by the platform on loan applications: the requested loan amount must be between € 500 and € 50,000; and the loan duration must be either 36 or 60 months. In addition, applicants may provide a description of the loan purpose, of their own personality and upload a picture. These additional pieces of information are provided voluntarily and are not verified by the platform.

Investors can browse through the applications and choose which borrower they want to finance. When an investor decides to provide funds to a particular borrower, he or she submits an electronic order. By submitting the order an investor "signs" a binding contract in which he/she commits to provide certain amount of money to the chosen borrower. The minimum acceptable order is € 250, the maximum is € 25,000. All orders must be multiples of 250. Often several investors submit offers to the same loan and each provides a fraction of the amount requested in the application. The number of investors tends to increase with the size of requested loan. So far, the average number of investors per loan was 15 and the median order is € 250.

An important distinguishing feature of *Smava.de* is that loans are *not* auctioned. In contrast to many other peer-to-peer lending sites, orders at this platform are accepted on the "first-come, first-served" basis, i.e. until the requested loan amount is covered to 100%. Investors cannot underbid offers from other investors by offering money at a lower interest rate. Money can only be provided under the terms specified in loan applications, i.e. under the interest rate and for the duration set by applicants.

Each application remains open for orders during 14 days, starting with the day when it was posted. If after this period less than 25% of the requested amount is raised, the application is canceled and the raised money (if any raised) is returned to investors.[7] The applicant can post the application again, eventually, offering more attractive conditions, e.g. a higher interest rate. In case of a successful brokerage, the platform charges investors with € 4 per order. Borrowers' fee depends on loan maturity and is 2 % of the borrowed sum (or at least € 40) when the loan is due in 36 months and 2.5 % of the borrowed sum (or at least € 60) if the loan matures in 60 months.[8]

Loans procured at the platform are installment credits that are not collateralized or guaranteed by third parties. Borrowers are only contractually bound to repay the debt and the interest in fixed monthly payments. To safeguard the investors from total loss, the platform utilizes two risk-reducing instruments. These instruments are described in more detail in the following sections of the paper.

### 4.3.3 What Information Do Investors Have?

Investing at the platform is characterized by substantial informational asymmetries between investors and borrowers. The asymmetries emerge mainly because borrowers' identity is not known and investors are provided with a limited set of information about the borrowers. Investors have access only to information that is collected and disclosed by the platform. Hence, ultimately the decisions of investors are built upon the provided information set.

Loan specific information observable to investors comprises the following details. Investors can observe in real time when a loan request is posted, what bids are submitted by the other investors (if any), when the submissions were made, and what share of the requested sum remains unfunded. Investors can also see the loan conditions set by borrowers: nominal annual interest rate, loan amount and maturity. Further, borrowers have to specify the purpose of loan by choosing an item from a menu of 17 categories. Figure 4.4 plots the distribution of applications over the categories. In addition to specifying the loan purpose, borrowers can also provide a relatively detailed description of the projects they need money for. This additional information should increase borrowers' trustworthiness and reduce informational asymmetries between the parties. However, the description of loan purpose is voluntarily and is not always provided.

The borrower-specific information observed by investors can be subdivided into "hard" and "soft" information. Hard information includes verified data that each borrower is obliged to provide. The data set comprises borrowers' age, sex, employment status, place of residence, credit rating, debt burden measured as debt-to-income ratio, number of delayed payments and defaults on previous *Smava* loans. Availability of hard information is crucial

[7] About 8% of loan applications in the data set did not raise any money; 5% raised less than 25% of requested amount; 6% raised $\geq$ 25% but less than 100%; 81% managed to raise 100% of requested amount.

[8] Smava changed the terms of the platform several times, but no changes were made during the time period under observation.

for investors, because it allows estimating the expected rate of return on investments and the probability of the borrower defaulting.

Although all pieces of hard information are verified, informational imperfections are still high. In particular, the platform provides only a rough estimate of borrowers' personal financial burden. The actual income and savings are not observable. Furthermore, nothing is known about the income and wealth of other household members. The available "hard" information is complemented by "soft" information. The latter is voluntarily provided by borrowers and is not verifiable. The "soft" data may include information on borrowers' education, hobbies, family status etc.

### 4.3.4 What Risks Do Investors Face?

Loans procured at the platform are neither secured by collateral nor guaranteed by third parties. Hence, investors can incur a loss if borrowers default on their obligations. To prevent total losses, the platform uses two instruments. Firstly, in case of default the claim to outstanding debt is sold to a collecting agency. Between 15 and 20 percent of invested capital can be recovered in this way. Secondly, a significantly larger part of capital can be recovered due to a risk sharing mechanism via loan pools.

Risk sharing via pools is accomplished by assigning investors into groups. Specifically, all investors who finance loans of the same duration and rating are assigned into one group. For example, all investors who granted loans to borrowers with rating "A" for 60 months belong to the same pool. Due to existence of 8 rating classes and 2 durations, there are 16 pools in total. Monthly redemption payments done by borrowers of the same pool are lumped together and each investor gets an amount proportional to his/her investment. Interest payments are not pooled together but transferred directly to investors. When some loans from the pool default, the losses are subtracted from the pool and the remainder is then divided among all members of the pool proportionally to their investments. In effect, all members of the pool including those who actually invested in the defaulted loan get a fraction of the usual monthly payment. This faction is called the *pool's payment rate*. For example, there are 100 investors in a pool and each granted a € 250-loan to different borrowers. If two loans get default, the pool's payment rate reduces to 98% which means that every member of the pool gets only 98% of the stipulated redemption payment. If another loan defaults, the pool's payment rate decreases to 97% and so on. The payment rate can, however, be improved when members of a pool invest in new loans of the same duration and rating and the old defaulted loans reach their maturity. The platform provides investors with a prediction of average payment rate for each pool (see Table 5.4). The described risk sharing mechanism assures that affected investors do not lose 100% of the invested capital. The flip side of the coin is that the losses are covered by withholding a part of cash inflows from the unaffected investors which reduces their profits.

Loans that are repaid prior to maturity present another source of risk. When a loan is repaid early, investors loose a part of expected interest payments. There is no penalty for early payments and, hence, investors get no compensation for the foregone interest. A further source of risk is associated with delayed payments. A delayed payment ties up the money and prevents investors from reinvesting it in new projects. Because no penalty for delayed payments is imposed on borrowers, lenders are not compensated for postponed reinvesting. Hence, delayed payments inflict losses in the form of foregone investment opportunities.

## 4.4 Research Hypothesis

The goal of the paper is to answer the question: Do females investing in p2p loans exhibit higher risk aversion than males? To answer this question, I analyze the choices of male and female investors.

At the considered market, the set of investment alternatives faced by investors is comprised of loans requested by loan applicants. In the following, I refer to loans as investment projects. An investor ranks his/her preferences over all available investment projects depending on how much utility he/she expects to obtain from each project. Specifically, I assume that investors have a two-parameter utility function $U(\mu, \sigma)$. That is, utility attached by an investor to a project depends on a linear combination of the project's expected return $\mu$ and its standard deviation $\sigma$. Thus, investors rank their preferences over different projects depending on the utility expected from them. If investors are rational, they choose to fund projects yielding the greatest utility. Hence, investor decision problem can be specified as choosing the projects with such combination of $\mu$ and $\sigma$ that maximizes investor utility.

Under these assumptions, investors' propensity for risk-taking can be measured relying on the $\mu$-$\sigma$ approach.[9] The intuition behind the $\mu$-$\sigma$ approach is that investors trade off between the expected return and its standard deviation whereas the latter represents risk. Investors like return and place a positive weight on $\mu$ so that $U(\cdot)$ increases in $\mu$. The weight placed by investors on $\sigma$ depends on the investors' individual risk preferences. Specifically, the weight is negative for risk-averse investors, so that $U(\cdot)$ decreases in $\sigma$. Moreover, the larger the weight the larger the decrease in utility. For risk-neutral investors, the weight is

[9] $\mu$-$\sigma$ approach is frequently criticized for its restrictive assumptions regarding the functional form of utility (Meyer, 1987; Bigelow, 1993) or distribution of returns (Chamberlain, 1983). However, in contrast to situations where mixtures of distributions are considered, in situations where preferences are to be ordered over a set of simple distributions (as is the case in this study), $\mu$-$\sigma$ approach can be employed under less restrictive assumptions (Meyer and Rasche, 1992).

Another restrictive property of $\mu$-$\sigma$ approach is its assumption that investors derive utility only from monetary payoffs of investment projects. However, recent studies show that individuals attach significant value to social returns of an investment (see e.g. Bollen, 2007; Benson and Humphrey, 2008). This circumstance is accounted for in the empirical part of the paper.

zero and $U(\cdot)$ does not depend on $\sigma$. For risk-loving investors, the weight is positive, so that $U(\cdot)$ increases in $\sigma$ and the larger the weight the larger the increase.

Hence, the effect of $\sigma$ on the expected utility differs among investors depending on individual risk preferences. This relationship provides the basis for the test of differences in risk preferences between male and female investors in the p2p credit market studied. Specifically, if females investing on the platform are on average more risk averse (or less risk lowing) than males, then they put a different weight on $\sigma$ than males. This implies that a marginal effect of $\sigma$ on the utility of a female investor differs from the marginal effect of $\sigma$ on the utility of male investors. In particular, if females are either more risk averse or less risk loving than males, then the difference between the marginal effect of $\sigma$ for females and males is negative. So, to answer the research question, the following hypothesis has to be tested:

***Hypothesis***: *Ceteris paribus, the difference between the marginal effect of $\sigma$ on the utility of a female investor and the marginal effect of $\sigma$ on the utility of a male investor is negative,*

$$\frac{\partial U_{Female}(\mu,\sigma)}{\partial \sigma} - \frac{\partial U_{Male}(\mu,\sigma)}{\partial \sigma} < 0.$$

Contrary, if males and females are, on average, equally risk prone then the effect on the utility should be the same for both genders implying no difference in the marginal effects. Moreover, if females are more risk prone than males than the difference in the marginal effects should be positive.

Hence, gender differences in risk propensity can be tested by estimating the marginal effect of one standard deviation of a project's expected return on the utility of investors. Inference about the utility attached by investors to different projects can be made based on the observed investment choices. The empirical test is described in the remainder of the paper.

## 4.5 Implementation of the Test

### 4.5.1 Econometric Model

Let $J_n^t$ denote the set of investment alternatives faced by investor $n$ in choice situation $t \in T_n$. $J_n^t$ comprises all investment projects that are available at the market at time $t$, when investor $n$ submits his/her order on one of the projects. The utility that investor $n$ attaches to investment project $j \in J_n^t$ can be decomposed in a deterministic part $\boldsymbol{\beta}_n' \mathbf{x}_{njt}$ which is a linear combination of the project's characteristics observable to researcher and an unobserved part, $\varepsilon_{njt}$:

$$U_{njt} = \boldsymbol{\beta}_n' \mathbf{x}_{njt} + \varepsilon_{njt}, \tag{4.1}$$

where $\mathbf{x}_{njt}$ is a $K$-dimensional vector of observable attributes of investment project $j$. The main characteristics of a project are the expected return and its standard deviation. Besides them, each project is characterized by a number of attributes summarized in Table 4.6. $\boldsymbol{\beta}_n$ is a vector of parameters reflecting investor's $n$ valuation of (or taste for) each attribute $k \in K$. $\varepsilon_{njt}$ is a stochastic term representing the random part of utility; it is *iid* over investors and choice situations. It is assumed that investor preferences are completely defined by the projects' attributes, that is, utility is derived from the attributes associated with investment projects rather than from projects *per se*. In line with this assumption, Equation 4.1 has no alternative-specific constants.

Vector $\boldsymbol{\beta}_n$ is explicitly allowed to vary over individuals. I assume that $\boldsymbol{\beta}_n$ is normally distributed with mean $\boldsymbol{b}$ and standard deviation $\boldsymbol{\sigma}_\beta$: $\boldsymbol{\beta}_n \sim N(\boldsymbol{b}, \boldsymbol{\sigma}_\beta)$.[10] This feature reflects the possibility that there is taste variation in the population and any given attribute of an investment project may receive different valuation from different investors. For example, utility derived from an investment project with a given expected return and standard deviation should vary over individuals depending on their risk preferences. However, preferences are not observed. Therefore, the model should accommodate *random* taste heterogeneity emerging due to unobserved investor-specific factors. Furthermore, a part of taste variation may also stem from observable differences among individuals such as, for example, age, income or gender. This kind of taste heterogeneity is *systematic* and can be explicitly modeled by taking investors' characteristics into account. Due to the research aim of this paper, I only focus on how valuation of projects' attributes depends on investor gender.

The two types of taste heterogeneity – random and systematic – are incorporated into Equation 4.1 by expressing vector $\boldsymbol{\beta}_n$ as a function of investors' gender and the unobserved individual-specific effects:

$$\boldsymbol{\beta}_n = \boldsymbol{b} + \boldsymbol{\gamma} Female_{njt} + \boldsymbol{\eta}_n,$$

where vector $\boldsymbol{b}$ has $k$-elements each representing the average valuation placed by male investors on project attribute $k \in K$. $Female_{njt}$ is a dummy variable equal 1 if investor is female and 0 if male.

Vector $\boldsymbol{\gamma}$ has $K$-elements each capturing the difference between the average effect of project attribute $k$ on the utility of a female investor and the marginal effect of project attribute $k$ on the utility a male investor. For instance, $\gamma_{SD[Return]}$ is one of the elements of $\boldsymbol{\gamma}$ that shows the difference between the effect of returns' standard deviation on the utility of females and the effect on the utility of males. With respect to the research hypothesis, $\gamma_{SD[Return]}$ is of central interest. A negative and statistically significant estimate $\widehat{\gamma_{SD[Return]}}$ means that females are more risk averse (or less risk tolerant) than males.

[10]I assume that coefficients of corresponding to different projects' attributes are not correlated. That is, the off-diagonal elements of matrix $\boldsymbol{\sigma}^2_\beta$ are zero.

$\boldsymbol{\eta}_n$ is a $K$-dimensional vector with elements representing the effect of unobserved factors associated with investor $n$ on his/her valuation of the project's attributes. Technically, $\boldsymbol{\eta}_n$ is a deviation of $\beta_n$ from its mean: $\boldsymbol{\eta}_n = \boldsymbol{\beta}_n - \boldsymbol{b}$. Therefore, it is by construction normally distributed with zero mean and standard deviation $\boldsymbol{\sigma}_\beta$. $\boldsymbol{\eta}_n$ is allowed to vary across investors but is assumed to be constant over choice situations for a given investor.

After specification of taste heterogeneity, Equation 4.1 can be rewritten as

$$U_{njt} = \boldsymbol{b}'\mathbf{x}_{njt} + \boldsymbol{\gamma} Female_{njt}\mathbf{x}_{njt} + \boldsymbol{\eta}_n\mathbf{x}_{njt} + \varepsilon_{njt}. \tag{4.2}$$

Now, the random portion of utility consists of $\boldsymbol{\eta}_n'\mathbf{x}_{njt} + \varepsilon_{njt}$. Due to the common effect of $\boldsymbol{\eta}_n$, the random term is correlated over investment alternatives and choice situations for a given investor.

So far, the equation describing investor choice has been specified so that expected utility enters the equation as a dependent variable. Yet, expected utility of an investor is his/her private information that is not observable to a researcher. What is observed is the choice set faced by an investor and the actual choice made. Assuming that investors are utility maximizers, it can be argued that the chosen project provides an investor with the greatest expected utility. Therefore, inference about factors affecting an investor's utility can be made by analyzing the relationship between observable attributes of investment alternatives and the investor's choice. Such analysis can be done by estimating a discrete choice model (Train, 2009).

Consider a data set where the unit of observation is an investment project. Each time an investor makes an investment, he/she contributes $N_{nt} = J_n^t$ observations to the data set, whereby $J_n^t$ is the number of projects entering the choice set of investor $n$ in choice situation $t$. Now, define a new binary variable $y_{njt}$ as follows

$$y_{njt} \begin{cases} = 1 & \text{if project } j \text{ is chosen by investor } n \text{ in situation } t \\ = 0 & \text{if project } j \text{ is not chosen} \end{cases}$$

The probability that investor $n$ chooses project $j$ in choice situation $t$ given projects' attributes is

$$Pr[y_{njt} = 1] \quad = \quad Pr[U_{njt} > U_{nit}, \, \forall\, j \neq i]$$

Brownstone and Train (1998) show that in the case when coefficient vector $\boldsymbol{\beta}_n$ entering the utility equation is randomly distributed with parameters $\boldsymbol{b}$ and $\boldsymbol{\sigma}_\beta$, the choice probability becomes

$$Pr[y_{njt} = 1] \quad = \int L_{njt}(\boldsymbol{\beta}_n) f(\boldsymbol{\beta}_n | \boldsymbol{b}, \, \boldsymbol{\sigma}_\beta) d(\boldsymbol{\beta}_n)$$

where $L_{njt}(\boldsymbol{\beta}_n)$ is given by a standard logit:

$$L_{njt} \quad = \frac{exp(\boldsymbol{b}'\mathbf{x}_{njt}+\boldsymbol{\gamma}Female_{njt}\mathbf{x}_{njt}+\boldsymbol{\eta}_n\mathbf{x}_{njt})}{\sum_i exp(\boldsymbol{b}'\mathbf{x}_{nit}+\boldsymbol{\gamma}Female_{nit}\mathbf{x}_{nit}+\boldsymbol{\eta}_n\mathbf{x}_{nit})}$$

Revelt and Train (1998) extend the model to situation where researcher observes repeated choices for a given decision-maker. Specifically, they show that the probability of a sequence of choices made by an individual is given by

$$Pr[y_{nj}=1] \quad = \int \prod^t L_{njt}(\boldsymbol{\beta}_n) f(\boldsymbol{\beta}_n | \boldsymbol{b},\, \boldsymbol{\sigma}_\beta) d(\boldsymbol{\beta}_n). \tag{4.3}$$

Models of this form are known in the literature as mixed logit (Train, 2009). As shown by McFadden and Train (2000) mixed logit models present a very flexible type of discrete choice models that allows efficient estimation of the parameters $\boldsymbol{b}$ and $\boldsymbol{\sigma}_\beta$ by means of maximum simulated likelihood.[11]

### 4.5.2 The Data Set

Data used to estimate Model 4.3 are collected from the publicly available electronic archives of *Smava.de*. The data set contains observations on the electronic orders submitted by investors between March 2007 and March 2010. The number of investors registered at the end of observation period was 5,671. The total number of submitted orders is 54,455. On average, each investor submitted 10 orders, meaning that on average each investor made a choice in 10 choice situations (the median is 4, the maximum is 292). In each choice situation, investors faced an average of 17 different investment projects (the median number of alternatives is 13, minimum is 1 and maximum is 84). Figure 4.8 plots the distribution of choice sets over the number of alternatives entering them.

The majority of investors participating on the platform are male. There are only 625 female investors, 11% of all registered investors.[12] Summary statistics in Table 4.5 reveal some differences in the profiles of male and female investors. Males started investing at

[11]Compared to other discrete choice models such as multinomial logit or probit models, mixed logit models exhibit a number of useful properties. For instance, in contrast to multinomial logit, mixed logit accommodates temporal correlation in error terms and relaxes the restrictive property of independence from irrelevant alternatives (IIA) (Train, 2009). Vis-a-vis multinomial probit model, estimation of mixed logit is computationally less demanding. Numerical methods of integration currently used for probit models (for instance, Gaussian quadrature) operate effectively only when the number of alternatives times the number of choice situations is no more than four or five (Train, 2009). Yet, the dimension of the data in hand is much higher. The number of choice situations alone amounts on average to 84, while the number of alternatives in a choice set is on average 17.

[12]The predominance of male investors at the platform suggests that some kind of self-selection is taking place. Unfortunately, the data do not allow modeling the selection mechanism and to identify what factors determine the participation decision. Previous research shows that women are usually under-represented in the financial markets. For instance, only 10% of managers in the investment fund industry are females (Beckmann and Menkhoff, 2008; Niessen and Ruenzi, 2007). Moreover, considering the financial markets at large, females are found to be less likely to invest in risky financial assets (Badunenko et al., 2009).

the p2p market 1 month earlier than females and hence can be said to be somewhat experienced than females. Female investors are, on average, 4 years older than male investors. The average amount invested per loan and the total amount invested at the platform by female investors is somewhat smaller than the respective amounts invested by male investors. However, the difference is statistically not significant.

For each submitted order the data includes information about the chosen loan application and the other applications entering the choice set of each investor. Attributes of loan applications that enter vector $\mathbf{x}_{njt}$ in Equation 4.2 are captured in the following variables. *Amount* is a continuous variable showing how much money a borrower requested in the application. Since the amount is always a multiple of 250 the variable is scaled by factor $\frac{1}{250}$ when used in regression analysis. *Duration* is a dummy variable equal 1 if loan is asked for 60 month and 0 if for 36 months. *Offered interest rate* is a continuous variable showing the nominal annual interest rate (in %) offered by a borrower. *Purpose* is a dummy variable equal 1 if a loan is taken for business purposes and 0 if for consumer purposes. *Description* is a continuous variable measuring the length of description of loan purpose provided by a borrower. This variable is equal to a logarithm of the number of characters used in the description. *Female* is a dummy variable describing borrowers' gender. It is equal 1 if borrower is female and 0 if male. *Age* is a continuous variable showing the age of borrower. Variable *Rating* takes on 8 values from "A" (the best creditworthiness) to "H" (the worst creditworthiness) and measures the creditworthiness of borrowers according to the scale of the German credit agency, Schufa. Dummy variable *Financial burden: low* is equal 1 if borrower's debt-to-income ratio does not exceed 20%. Dummy variable *Financial burden: moderate* equals 1 if debt-to-income ratio lies within the range 20-40% and 0 otherwise. Dummy variable *Financial burden: substantial* equals 1 if debt-to-income ratio lies within the range 40-60%. Dummy variable *Financial burden: high* equals 1 if debt-to-income ratio lies within the range 60-67%. *Employment* is a dummy variable indicating borrowers' employment status. It is equal 1 if borrower is self-employed, and 0 if borrower is either employed or retired.

Information about projects' expected return and variance of returns is not provided to either investors or researchers. Both must calculate these attributes individually. Calculation of expected return and its standard deviation, as applied in this study, is described in the next section.

### 4.5.3 Calculation of expected return and its variance

Assuming that the uncertainty pertaining to the payoff of an annuity loan stems only from the probability that a borrower defaults,[13] then investing in an annuity loan can be seen as

[13] There are other sources of uncertainty such as the probability of early repayment of a loan or changes in the payment rates of pools. However, the present analysis does not take these into account.

buying a lottery with $M+1$ possible outcomes where $M$ equals to the number of monthly installments that a borrower is contractually obliged to pay in order to repay the loan. Depending on when a borrower defaults, the number of actually paid installments can vary between 0 (no payments made) and $M$ (all payments completed). Realization of any of $M+1$ outcomes determines what rate of return to investment is obtained. The rate of return, conditional on realization of an outcome, is denoted by $R_m$.

Probability of each outcome of the lottery is determined by the probability that a borrower defaults and does not pay back a number of installments. Let $T = \{1, 2, ..., M\}$ be a discrete random variable indicating the sequential number of installment at which a default occurred, i.e. neither the installment in question nor any of the subsequent installments are paid. Let $f(t)$ denote the probability distribution function of $T$. Then, probability of default occurring with installment $t$ is $Pr(T=t) = f(t)$. The probability distribution function $f(t)$ is not known. However, it can be estimated based on the payment behavior of borrowers observed in the past. In particular, it is helpful to estimate how probability of default with any given installment depends on the observable characteristics of borrowers and loan terms. Procedure used to estimate the probabilities is described in Appendix A. Based on estimated default probabilities, one obtains estimates of the probability of each outcome for any given loan, $\hat{p}_1, ..., \hat{p}_{M+1}$.

Figure 4.5 illustrates the possible outcomes and the respective probabilities for a loan with duration 36 months. The duration of 36 months implies that a borrower must pay 36 installments. Respectively, there are 37 possible outcomes. Let $R_1$ denote the rate of return received by investor if the first outcome is realized. The first outcome is realized if borrower does not pay any installments. The probability of this outcome, $p_1$, is the probability that default occurs with the first installment, $Pr(T=1) = f(2)$. The second outcome is realized if borrower pays the first installment but defaults with the second installment. This outcome occurs with probability $p_2 = Pr(T=2) = f(2)$. And so on. Finally, the last possible outcome emerges if borrower makes all payments, i.e. does not default on any of the installments. The probability of this event $p_{37} = Pr(T \geq 36) = 1 - f(36)$.

The next step is to determine the rate of return, $R_m$, generated in case of each outcome. Return to an annuity loan can be determined by calculating the internal rate of return from a series of cash flows produced by the loan. Similar to a common annuity loan, cash flow generated by a *Smava*-loan is given by a series of monthly installments paid by borrowers whereby each installment consists of debt redemption and interest on the outstanding debt. With *Smava* loans, even in case of a borrower default, investors receive some money back due to the collective insurance mechanism described in Section 4.3. Investors always get a fraction of the contractually stipulated redemption regardless of whether a borrower defaults or not. This fraction is determined by the payment rate of the pool the investor belongs to,

$P_p$.[14] Interest is exempt from the insurance mechanism, such that investors do not get any of the contractually stipulated interest if their borrowers default.

Hence, amount $A_t$ received by an investor at the $t$-th month of a loan duration is

$$A_t = \begin{cases} P_p \times D_t + I_t, & \forall t < T \\ P_p \times D_t, & \forall\, t \geq T. \end{cases}$$

where $D_t$ is the value of contractually stipulated redemption in month $t$, $P_p$ is the repayment rate of pool $p$ where investor belongs to, $I_t$ is the contractually stipulated interest in month $t$, and $T$ is the installment at which a default occurred.

Then, return $R_m$ generated by a loan if outcome $m$ is realized is obtained by solving for $r$ in

$$\begin{aligned} Investment{+}Fee &= \textstyle\sum_{t=1}^{M} \frac{P_p \times D_t}{(1+r)^t}, && \text{if } m = 1 \\ Investment{+}Fee &= \textstyle\sum_{t=T}^{M} \frac{P_p \times D_t}{(1+r)^t} + \sum_{t=1}^{T-1} \frac{I_t}{(1+r)^t}, && \text{if } 1 < m < M+1 \\ Investment{+}Fee &= \textstyle\sum_{t=1}^{M} \frac{P_p \times D_t + I_t}{(1+r)^t}, && \text{if } m = M+1 \end{aligned}$$

where *Investment* is the amount invested in the loan by a particular investor and *Fee* is the fixed fee charged by the platform for each investment.[15]

The expected return from a loan is given by a weighted sum of returns associated with all $M+1$ outcomes with weights given by the probabilities, $\hat{p}_1, ..., \hat{p}_{M+1}$:

$$E[Return] = \sum_{m=1}^{M+1} p_m \times R_m.$$

Figure 4.6 plots the distribution of annualized $E[Return]$ over all investment projects posted on the market. The sample mean of annualized $E[Return]$ is 6.8%.

The measure of returns variation given by the standard deviation in return is calculated as follows

$$SD[Return] = \sqrt{\sum_{m=1}^{M+1} p_m \times (R_m - E[Return])^2}$$

[14] In reality, payment rate of each pool varies depending on how many loans in the pool default in a given month. However, because at the moment of investment investors do not know the future rates, they have to rely on some assumptions regarding the process. In my calculations, I make a simplifying assumption that payment rate remains constant at the level as predicted by the platform. See Table 5.4.

[15] Presence of a fixed fee implies that the return depends on the investment amount. However, because the fee is very small relative to the minimal possible order, the effect should be negligible. So the calculations are done assuming that each investor allocates the minimal possible amount of 250 Euro per loan. Then, it is sufficient to calculate the return for (only) 3,354 loan applications instead of all 54,455 investments done at the platform. Because calculation of return involves computationally intensive optimization procedure, reducing the number of cases is crucial.

Figure 4.7 plots the calculated $SD[Return]$ against $E[Return]$ for all investment projects posted on the market. The calculated $SD[Return]$ and $E[Return]$ are further used as explanatory variables entering vector $\mathbf{x}_{njt}$ in Equation 4.2.

### 4.5.4 Estimation Results

Results of the estimation of Model 4.3 are reported in Table 4.7. Note that there are three different blocks of estimated parameters: $\hat{\boldsymbol{b}}$, $\hat{\boldsymbol{\sigma}}_\beta$ and $\hat{\boldsymbol{\gamma}}$. $\hat{\boldsymbol{b}}$ is an estimate of the vector of random coefficients $\boldsymbol{\beta}_n$; it represents the average effect of respective variables on the expected utility of male investors. $\hat{\boldsymbol{\sigma}}_\beta$ is the estimated standard deviation of $\boldsymbol{\beta}_n$ reflecting the variation of tastes among investors. The estimate $\hat{\boldsymbol{\gamma}}$ is the parameter of primary interest; it shows how the average effect of variables on the utility of female investors differs from the effect of these variables on the utility of male investors.

Results reported under the header "*S1*" are obtained for a reduced specification of the vector of random parameters $\boldsymbol{\beta}_n$ and the vector of explanatory variables $\mathbf{x}_{njt}$. Specifically, $\boldsymbol{\beta}_n = \boldsymbol{b} + \boldsymbol{\eta}_n$ while $\mathbf{x}_{njt}$ includes only two variables $E[Return]$ and $SD[Return]$. This specification does not take into account investors' gender. However, it allows seeing how investors respond to projects' expected return and variation. The estimate of the mean of the coefficient for $E[Return]$ is 0.79 and is statistically significant implying that expected utility of a project increases with $E[Return]$, holding other characteristics of the project constant. The estimate of the standard deviation of the coefficient for $E[Return]$ is 0.528 and is statistically significant. This means that there is considerable variation in investors' responses to the level of projects' return. For a small fraction of investors the coefficient is even negative.[16] This result does not necessarily imply that investors dislike higher returns. Rather it signals that a fraction of investors rely on a decision rule different from the mean-variance principle. Moreover, in the context of peer-to-peer lending, investors may derive significant utility from social returns stemming from awareness that invested money will be used for a socially useful project or help another person out in a difficult situation. Respectively, individuals may engage more willingly in less profitable projects if such projects are associated with substantial social returns.

The estimate of the mean of the coefficient for $SD[Return]$ is negative (-0.267) and statistically significant, which indicates that on average investors dislike variation in returns. The probability of investing in a project decreases in response to a marginal increase in return's variation. Hence, the majority of investors on the p2p platform seem to be risk-averse. The estimate of the standard deviation of the coefficient for $SD[Return]$ is statistically significant meaning that preferences for returns' variance vary in the population. Moreover,

[16] This inference is derived from the properties of normal distribution. Because coefficients are assumed to be normally distributed, 68% of investors fall within the range between $-\sigma$ and $+\sigma$; 95% of investors fall within the range between $-2\sigma$ and $+2\sigma$; and 99% of investors fall within the range between $-3\sigma$ and $+3\sigma$

the magnitude of the standard deviation implies that for a considerable number of investors higher variation in returns is associated with higher expected utility. Again, this result may emerge because not all investors consider mean-variance rule as a criterion for investment choice. Or, alternatively, the finding may indicate that a portion of investors are risk-loving.

Results reported under the header "*S2*" are obtained for the same specification of $\beta$ as before, but this time vector $\mathbf{x}_{njt}$ is extended by including other observable characteristics of loan projects. Previously received results for the effects of $E[Return]$ and $SD[Return]$ remain basically unchanged: Utility of investors is positively related to investments' return and negatively related to the variation of return. However, the magnitude of the estimates of the means of the two coefficients decreased compared to results for the baseline specification. Because of the way the expected return and its variance are calculated in the study, they depend on the attributes of the projects. When the attributes are additionally included in the regression equation together with $E[Return]$ and $SD[Return]$, it can lead to multicollinearity and respectively reduce the significance ascribed to $E[Return]$ and $SD[Return]$. Moreover, the fact that all considered attributes have significant effect on investors' utility indicates that investors attach significant value to the attributes in addition to the impact these factors have on return and its variation. For example, the coefficient estimate for the dummy variable *Loan duration=60 months* is -1.067 meaning that investors prefer short term loans over long term loans. Even when investors realize that, *ceteris paribus*, return is negatively linked to loan duration they may attach additional negative value to long durations simply because they dislike it when their money is tied up for a long time.

Finally, results under the header "*S3*" relate to an extended specification when $\boldsymbol{\beta}_n = \boldsymbol{b} + \boldsymbol{\gamma} Female_{ijt} + \boldsymbol{\eta}_n$. This specification allows the effect of projects' attributes to vary with investors' gender. The main parameters of interest are reported in the lower part of the table under $\hat{\boldsymbol{\gamma}}$. Coefficient estimates for $E[Return]$ and $SD[Return]$ are statistically insignificant meaning that the effect of one standard deviation of project's return on utility of female investors is not different from the effect on utility of male investors. Hence, contrary to the research hypothesis, a marginal increase in returns variability reduces the utility of a female investor as much as it reduces the utility of a male investor. Also borrowers' rating and financial burden – the two characteristics that might be considered by investors as a rough proxy for investments' riskiness – has the same effect for females as for males. Therefore, the results do not confirm that gender has an effect on investor risk taking propensity.

However, some significant gender differences in investor tastes are found with respect to other attributes of investment projects. For instance, females seem to dislike long-term loans more than males. Unlike males, females prefer consumer loans over business loans. The only borrower-specific characteristic where female investors seem to have different tastes than males is borrower age: Utility derived by females increases with borrower age. However, this result may be driven by the fact that female investors participating at *Smava* are, on average, somewhat older than male investors. Noteworthy, the effect of borrowers' gender does not vary with investors' gender. Hence, both male and female investors are more willing to provide funds to female borrowers than to male borrowers.

## 4.6 Conclusions

This paper examines the role of investor gender in their propensity for risk taking when investing on an online p2p credit market. A p2p market serves as a channel though which investors directly allocate capital to investment projects without intermediation of a financial institution or advisor. Because payoffs from loans are uncertain, p2p loans can be seen as a form of risky investment. Investors' choices allow making inference about their risk preferences.

A comparison of investment choices of male and female investors participating in p2p-lending does not reveal any significant differences with respect to their risk propensity. Relying on the mean-variance framework, I test whether female investors respond to increasing variance in expected returns differently than male investors. The results of a test show that gender does not matter for investors' risk preferences. A marginal increase in the standard deviation of expected return equally affects the utility of males and females. Moreover, no differences between male and female investors are found with respect to other characteristics of projects that may serve as proxy for projects' riskiness. Hence, the data on peer-to-peer lending do not support the conjecture that women tend to take less risks in investment decisions than their male counterparts.

However, the results should be enjoyed with caution because low participation of females in the market indicates self-selection. If probability of investing at the market is correlated with individual risk-propensity, then obtained results cannot be generalized to the overall population. Nevertheless, the study provides useful evidence on the behavior of individuals who are likely to self-select into risk-taking activities. A conclusion that can be derived from this perspective is that gender seems to play no role in the behavior of individuals who deliberately engage in risk-taking. Hence, the results are consistent with studies showing that, among professionally trained investors, females behave similarly to males with respect to risk (Johnson and Powell, 1994; Atkinson et al., 2003). The present study supports and extends this literature by showing that this relationship holds also in self-selected groups of not-trained retail investors.

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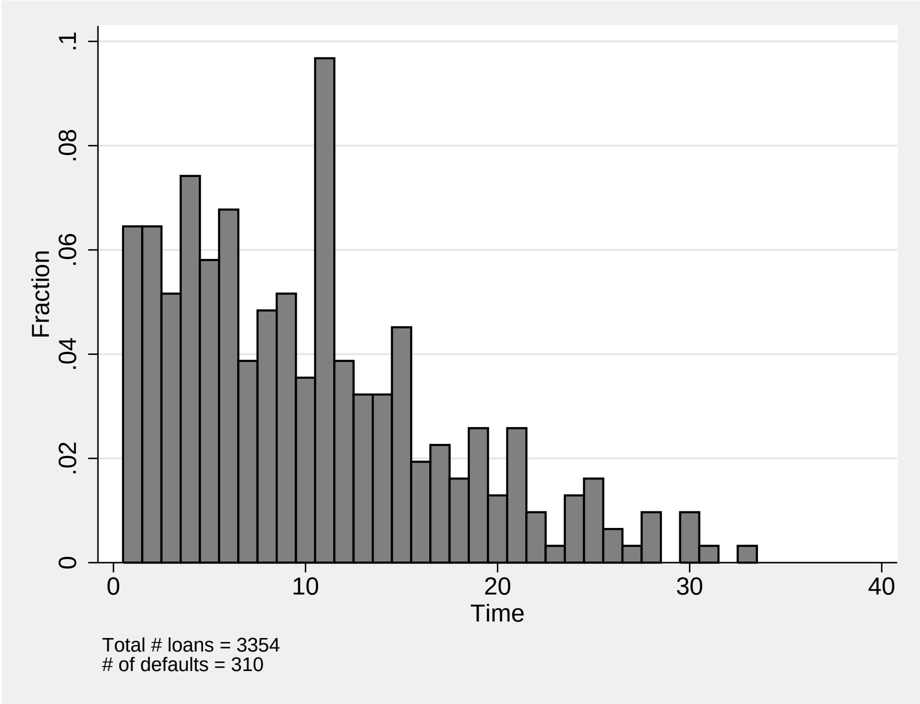
# Appendix A: Estimation of the probability of default

Probability of default in a given month of a loan's duration is estimated using the observed payment behavior of borrowers at *Smava*. Information about borrowers' payment behavior is collected from http://www.beobach.de/. Repayment history is observed through the end of December 2010. Figure 4.1 plots distribution of defaults by the month of default observed in the data. Since the market is young, many credits have not matured yet. Specifically, of 3,354 loans that were granted between March 2007 and March 2010, 386 were repaid (including early repayments) and 310 defaulted by the end of December 2010.

Figure 4.1: Distribution of defaults by month of default




$T$ is the discrete random variable indexed by a set of positive integers $T = \{1, 2, 3, ..., M\}$ indicating the installment at which a default occurred. Let $f(t)$ denote the probability distribution function of $T$ and $F(t)$ denote the cumulative probability function describing the probability that $T \leq t$. Let $S(t)$ denote the survival function of $T$ describing the probability that default occurs at some time after month $t$. Essentially, the survival function shows the probability that a borrower serves the debt for at least $t$ months. The relationship of $S(t)$ to $f(t)$ is straightforward: $S(t) = Pr(T > t) = 1 - F(t) = 1 - \sum_{t=1}^{T} f(t)$.

Now, denote the conditional probability that a default occurs in month $t$ conditional on the probability that the debt was timely served during $t-1$ months, as $h(t)$. This conditional probability is known as the discrete-time hazard rate and is linked to the survival probability in the following way

$$h(t) = Pr[T = t | T \geq t] = \frac{f(t)}{S(t-1)}.$$

As shown by Jenkins (1995), $h(t)$ can be estimated using conventional estimation methods for binary response variables. In order to do so, the data are organized such that the unit of observation is the monthly payment and not a loan. Each loan contributes as many observations to the data set as there are monthly payments done by a borrower to repay the loan.

Define a new binary indicator variable $y_{it}$ with $y_{it} = 1$ if loan $i$ defaults in month $t$ and $y_{it} = 0$ otherwise. Note that $Pr(y_{it} = 1 | T \geq t) = Pr[T = t | T \geq t] = h_i(t)$. Hence, log-likelihood of observing the data is

$$\log L = \sum_{i=1}^{N} \sum_{t=1}^{T} \left[ y_{it} \log(h_i(t)) + (1 - y_{it}) \times \log(1 - h_i(t)) \right].$$

All that is needed now to estimate the hazard rate is a functional specification of $h(t)$. The most commonly used specification is the logistic hazard function (Cox, 1972; Jenkins, 1995). Logistic distribution of the hazard rate implies that $h(t)$ can be estimated by means of a logit regression:

$$h(t|X) = \frac{\exp(\alpha_0 + \alpha_1 \ln(t) + \beta X)}{(1 + exp(\alpha_0 + \alpha_1 \ln(t) + \beta X)}. \tag{4.4}$$

Time dependence of the hazard rate is operationalized by including a logarithmic function of time, $\alpha_1 ln(t)$ into the model. Such specification of duration dependence implies a monotonically decreasing hazard if $\alpha_1 < 0$, a monotonically increasing hazard if $\alpha_1 > 0$, and a constant hazard if $\alpha_1 = 0$. The effect of observable characteristics included in vector $X$ is captured in parameters' vector $\beta$. Vector $X$ includes the following variables: raised loan amount (divided by 250), offered interest rate in % p.a., loan duration, loan purpose, borrower's Schufa-rating with "A" being the best grade, financial burden, employment status, age, gender, place of residence, loan vintage (year and quarter when the first payment is due) and calendar month of payment to capture seasonality effects. Note that only observations on approved loans can be used to estimate equation 4.4. Estimation results are reported in Table 4.1. According to the results, $\hat{\alpha}_1 = -0.150$. Thus, $\hat{h}(t|X)$ decreases with the time.

Table 4.1: Estimation results after discrete-time hazard model

| | Coeff. | St.Error |
|---|---|---|
| Raised amount | 0.009*** | (0.00) |
| Offered interest rate | 0.166*** | (0.04) |
| Loan duration | | |
| 36 months (ref.) | | |
| 60 months | 0.147 | (0.15) |
| Rating | | |
| A | | |
| B | 0.544* | (0.33) |
| C | 0.250 | (0.38) |
| D | 0.422 | (0.37) |
| E | 0.590* | (0.35) |
| F | 0.636* | (0.35) |
| G | 0.746** | (0.37) |
| H | 0.889** | (0.42) |
| Financial burden | | |
| low (ref.) | | |
| moderate | 0.870** | (0.35) |
| substantial | 0.863*** | (0.33) |
| high | 1.076*** | (0.33) |
| Employment | | |
| Arbeiter/Angestellter (ref.) | | |
| Beamter | -1.135* | (0.61) |

| | | |
|---|---|---|
| Freiberufler | -0.985*** | (0.33) |
| Geschäftsführer | 0.044 | (0.29) |
| Gewerbetreibender | 0.026 | (0.18) |
| Rentner | 0.374 | (0.30) |
| Age | -0.001 | (0.01) |
| Gender | | |
| Male (ref.) | | |
| Female | 0.078 | (0.14) |
| Loan purpose | | |
| Aus- & Weiterbildung | -0.001 | (0.37) |
| Auto & Motorrad | 0.301 | (0.21) |
| Familie & Erziehung | -0.051 | (0.24) |
| Feierlichkeiten & besondere Anlässe | -0.290 | (0.52) |
| Geschäftserweiterung | -0.439 | (0.38) |
| Gesundheit & Lifestyle | -0.027 | (0.44) |
| Gewerblicher Kreditbedarf | -0.358 | (0.46) |
| Haus, Garten, Heimwerken (ref.) | | |
| Investition | -0.402 | (0.66) |
| Liquidität | 0.158 | (0.26) |
| Reisen & Urlaub | -0.268 | (0.48) |
| Sammeln & Seltenes | | |
| Sonstiges | 0.297 | (0.21) |
| Sport & Freizeit | 0.380 | (0.38) |
| Tierwelt | 0.847** | (0.42) |
| Umschuldung | 0.088 | (0.25) |
| Unterhaltungselektronik & Technik | 0.415 | (0.37) |
| Place of residence | | |
| Baden-Württemberg | 0.036 | (0.23) |
| Bayern | -0.410* | (0.23) |
| Berlin | 0.157 | (0.28) |
| Brandenburg | 0.087 | (0.37) |
| Bremen | | |
| Hamburg | 0.550 | (0.36) |
| Hessen | 0.326 | (0.23) |
| Mecklenburg-Vorpommern | 0.242 | (0.49) |
| Niedersachsen | 0.241 | (0.25) |
| Nordrhein-Westfalen (ref.) | | |
| Rheinland-Pfalz | 0.324 | (0.30) |
| Saarland | -0.724 | (1.03) |
| Sachsen | 0.672*** | (0.26) |
| Sachsen-Anhalt | 0.436 | (0.39) |
| Schleswig-Holstein | 0.841*** | (0.26) |
| Thüringen | 0.613* | (0.35) |
| Season | | |
| Jan (ref.) | | |
| Feb | 1.126*** | (0.33) |
| Mar | 0.608* | (0.36) |
| Apr | 0.920*** | (0.34) |
| Mai | 0.670* | (0.35) |
| Jun | 0.430 | (0.36) |
| Jul | 0.930*** | (0.33) |
| Aug | 0.149 | (0.38) |
| Sep | 0.720** | (0.34) |
| Okt | 0.549 | (0.35) |
| Nov | 0.620* | (0.34) |
| Dec | -0.198 | (0.39) |
| Vintage | | |
| 2007q2 (ref.) | | |
| 2007q3 | 0.282 | (0.87) |
| 2007q4 | -0.316 | (0.82) |
| 2008q1 | -0.039 | (0.81) |
| 2008q2 | -0.023 | (0.80) |
| 2008q3 | 0.207 | (0.81) |
| 2008q4 | 0.076 | (0.81) |
| 2009q1 | -0.235 | (0.81) |
| 2009q2 | 0.142 | (0.80) |
| 2009q3 | -0.076 | (0.81) |
| 2009q4 | -0.597 | (0.82) |
| 2010q1 | -0.765 | (0.84) |
| 2010q2 | -0.716 | (1.07) |
| ln(t) | -0.150** | (0.06) |
| Constant | -9.263*** | (1.00) |

| | |
|---|---|
| Pseudo-$R^2$ | 0.096 |
| N | 56589 |

* p<0.10, ** p<0.05, *** p<0.01
(ref.) = reference category

Using the vector of estimated coefficients, I calculate for each loan application posted at the platform (not only the approved ones) its individual hazard function, $\hat{h}_l(t)$. Based on the determined hazard function, the survival function $\hat{S}_l(t)$ and the probability distribution function $\hat{f}_l(t)$ are calculated for each loan application:

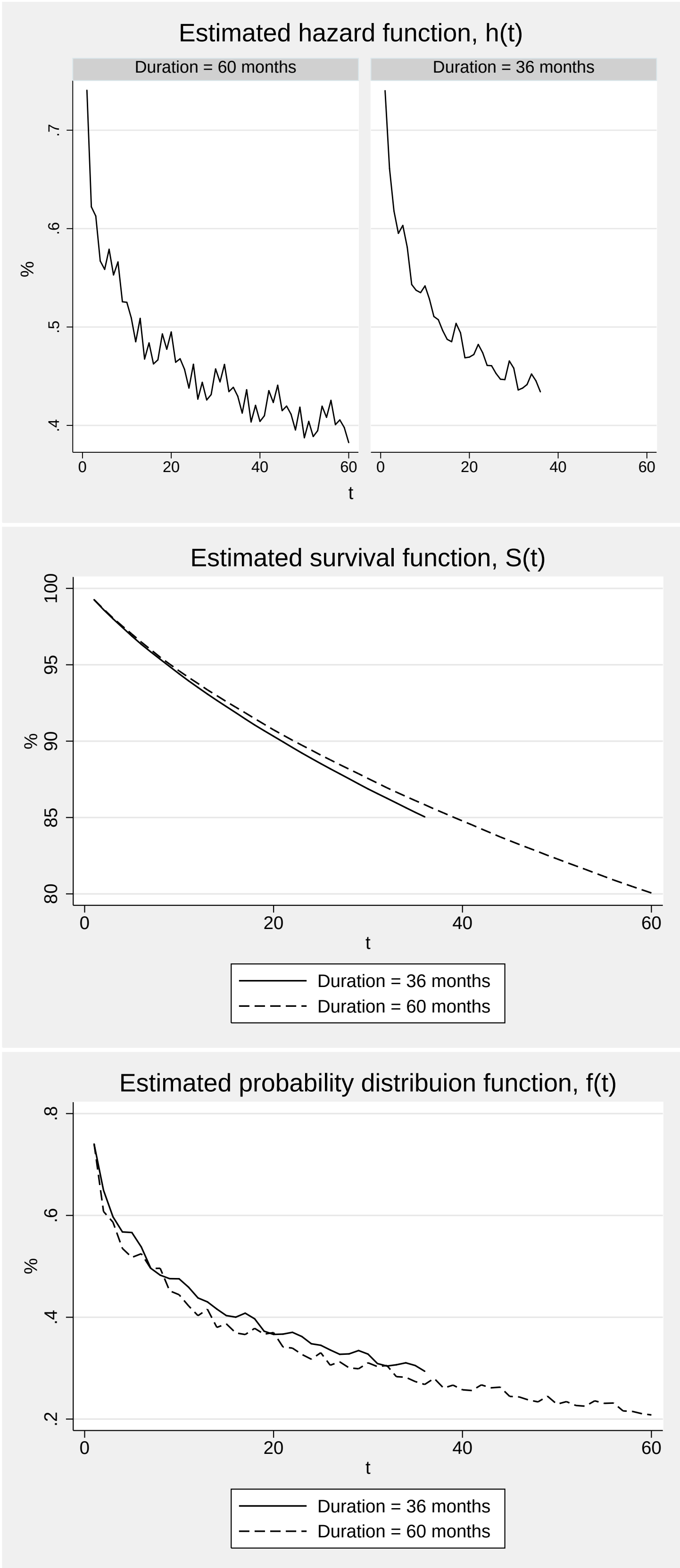
$$\hat{S}_l(t) = \prod_{j=1}^{t}(1-\hat{h}_l(j)),$$

$$\hat{f}_l(t) = \begin{cases} 1-\hat{S}_l(t), & \text{if } t = 1 \\ \hat{S}_l(t-1)-\hat{S}_l(t), & \text{if } t > 1. \end{cases}$$

The sample means for the hazard, survival and probability distribution functions are plotted in Figure 4.2. Estimated probability distribution function of loan $l$, $\hat{f}_l(t)$, is used to determine $p_{1l},...,p_{M+1l}$ – the probability of each possible outcome from loan $l$:

$$\hat{p}_{tl} = \begin{cases} \hat{f}_l(t), & \forall\, t < M+1 \\ 1-\sum_{t=1}^{M}\hat{f}_l(t), & \text{if } t = M+1. \end{cases}$$

Figure 4.2: Estimated functions



# Appendix B: Figures and Tables

Figure 4.3: Loans procured at *Smava*

This graph plots cumulative distribution of the number and the volume of loans procured at the platform between March, 2007 and March, 2010

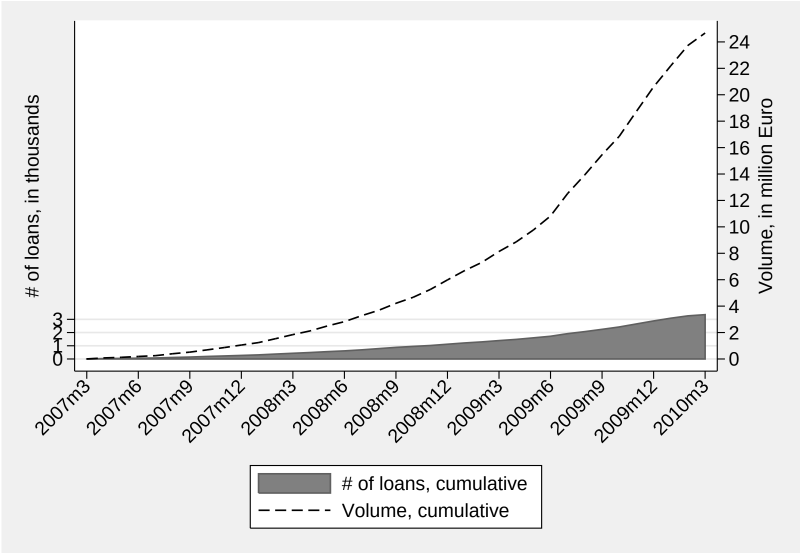



Figure 4.4: Distribution of loan applications by loan purpose

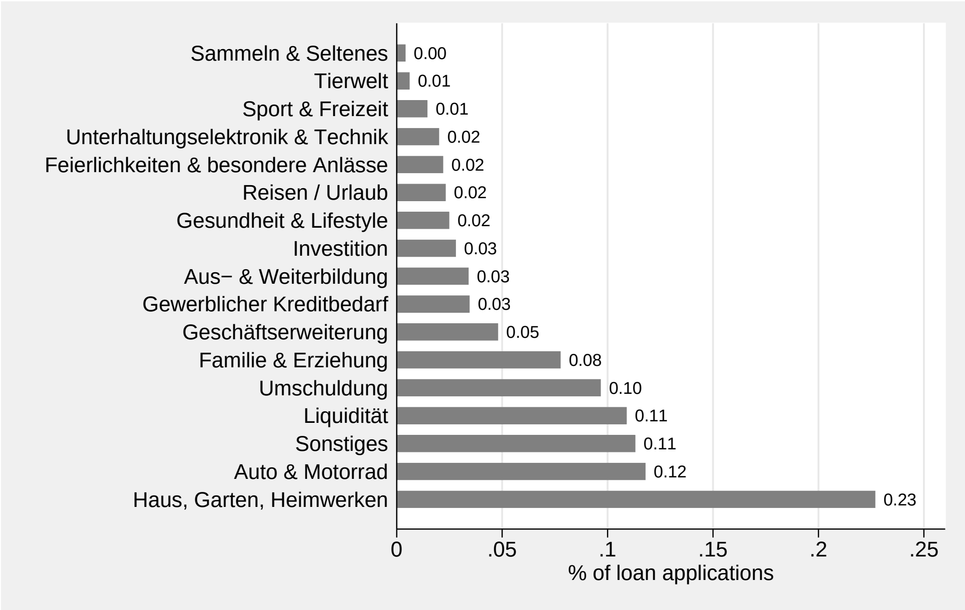


Figure 4.5: Possible outcomes of investment in a loan with duration 36 months

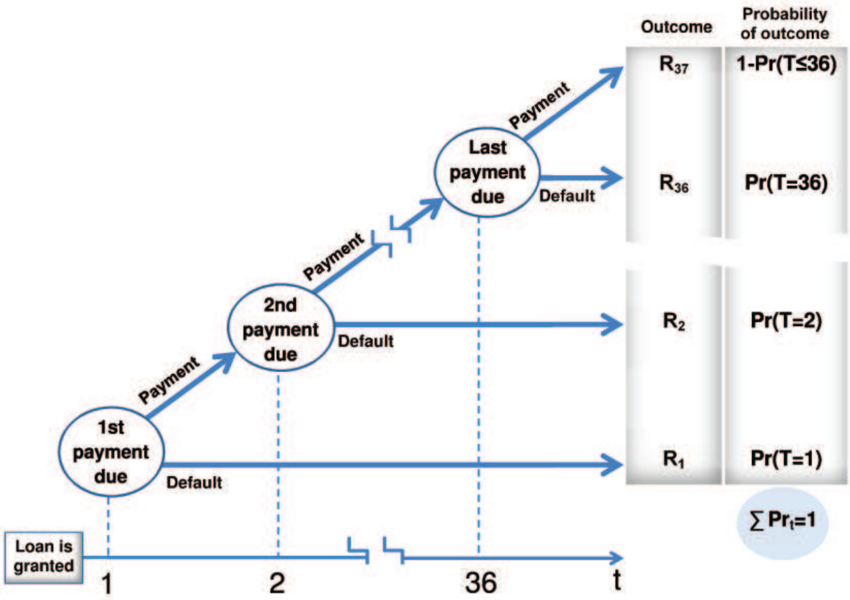



Figure 4.6: Distribution of expected return over projects

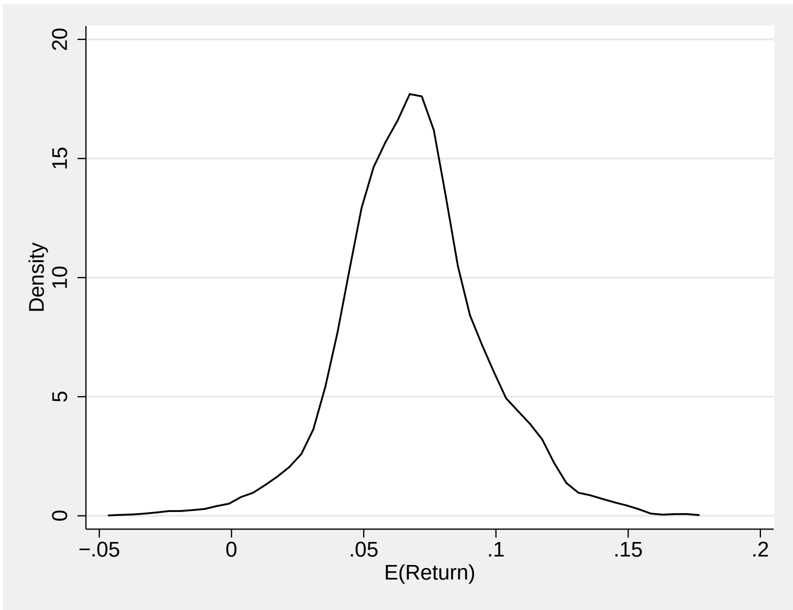


Figure 4.7: Standard deviation of return plotted against the expected return

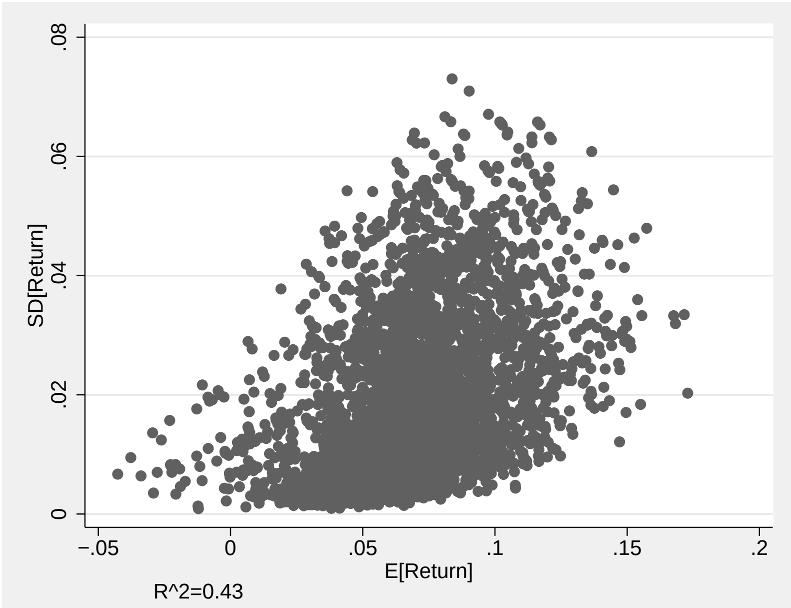



Figure 4.8: Distribution of choice sets by the number of alternatives in a set

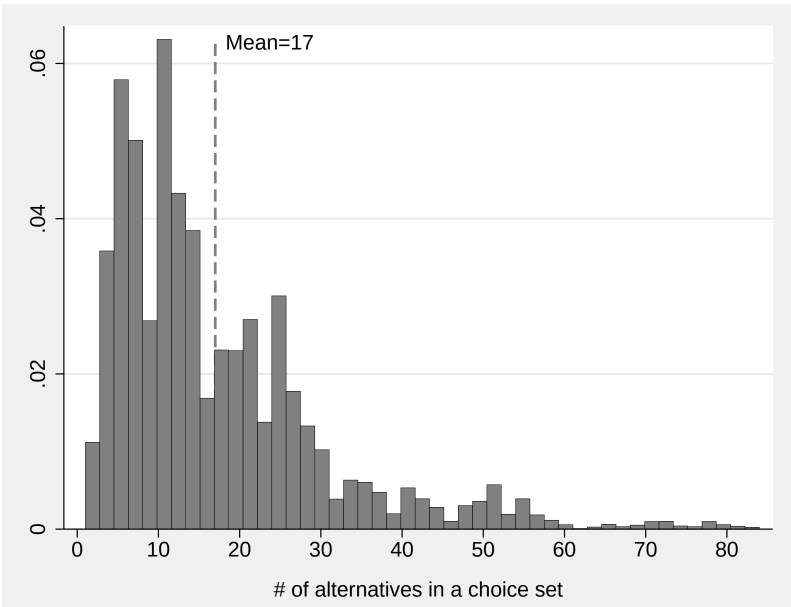


Table 4.2: KDF-Indicator

| KDF-Indikator | Debt-to-disposable income ratio |
|---|---|
| 1 | 0 bis 20% |
| 2 | 20 bis 40% |
| 3 | 40 bis 60% |
| 4 | 60 bis 67% |

Table 4.3: Creditworthiness rating grades and corresponding PDs

This table shows the rating grades that eligible individuals to borrow at the platform. The rating grades are assigned to borrowers by the German national credit bureau *Schufa*. Each rating grade reflects the probability of a borrower's default given his past credit behavior and current debt obligations.

| Rating grade | Probability of default | Fraction of loans with given rating grade |
|---|---|---|
| A | 1.38 | 15.91 |
| B | 2.46 | 16.21 |
| C | 3.56 | 10.16 |
| D | 4.41 | 9.94 |
| E | 5.57 | 10.83 |
| F | 7.16 | 12.30 |
| G | 10.72 | 14.77 |
| H | 15.02 | 9.88 |

Table 4.4: Historical payment rates in pools

This table shows the predicted and the historical average payment rate for each of the 16 pools. The historical average is calculated over the period from April 2007 to January 2010. Source: http://www.smava.de.

| | **Loans with duration 36 months** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | F | G | H |
| Predicted payment rate | 98.8 | 97.8 | 96.6 | 96.1 | 95.1 | 93.7 | 90.6 | 87.1 |
| Historical average | 97.4 | 95.8 | 98.4 | 95.6 | 95.9 | 92.4 | 92.0 | 89.7 |
| | **Loans with duration 60 months** | | | | | | | |
| | A | B | C | D | E | F | G | H |
| Predicted payment rate | 98.5 | 97.4 | 95.8 | 95.4 | 94.2 | 92.4 | 88.8 | 84.6 |
| Historical average | 99.5 | 97.8 | 98.5 | 91.5 | 95.2 | 94.2 | 85.9 | 84.1 |

Table 4.5: Summary statistics of selected variables by investors' gender

| Variable | Males N=5,046 | | Females N=625 | | | |
|---|---|---|---|---|---|---|
| | Mean | St.Dev. | Mean | St.Dev. | t-Test | p-value |
| Age | 41 | 12.32 | 45 | 12.50 | -6.31 | 0.00 |
| Duration of participation | 14 | 8.72 | 13 | 7.80 | 3.81 | 0.00 |
| # of submitted orders | 10 | 16 | 8 | 12 | 2.24 | 0.02 |
| Order value, in € | 469 | 372 | 481 | 391 | -0.80 | 0.42 |
| Total amount invested | 4,436 | 8456 | 4,004 | 7165 | 1.74 | 0.25 |

Table 4.6: Definition of explanatory variables

| Variable Name | Description |
|---|---|
| **Investor-specific characteristics** | |
| Female | = 1 if investor is female, = 0 otherwise |
| **Loan-specific characteristics** | |
| E(Return) | Expected rate of return to investment, in % p.a. |
| SD(Return) | Standard deviation of the expected rate of return form investment |
| Amount[a] | Requested loan amount, in €. |
| Duration=60 months | Dummy variable = 1 if loan duration is 60 months, = 0 if 36 months |
| Offered interest rate | Offered nominal annual interest rate, in % |
| Purpose | =1 if business loan, =0 if consumer loan |
| Description | Length of description of loan purpose, in # of characters |
| **Borrower-specific characteristics** | |
| Age | Age in years |
| Female | = 1 if borrower is female, = 0 if male |
| Rating | measures borrowers' creditworthiness, takes 8 values from A (best) to H (worst) |
| Financial burden: low | = 1 if borrower's debt-to-income ratio does not exceed 20% and 0 otherwise |
| Financial burden: moderate | =1 if debt-to-income ratio lies within the range 20-40% and 0 otherwise |
| Financial burden: substantial | =1 if debt-to-income ratio lies within the range 40-60% and 0 otherwise |
| Financial burden: high | =1 if debt-to-income ratio lies within the range 60-67% and 0 otherwise |
| Employment | =1 if borrower is self-employed 0 if employed or retired |

[a] Since the value is always a multiple of 250, the variable is scaled by factor $\frac{1}{250}$ when used in regressions

Table 4.7: Estimation results after mixed logit regression

| | S1 | | S2 | | S3 | |
|---|---|---|---|---|---|---|
| | Estimate | St.Error | Estimate | St.Error | Estimate | St.Error |
| $\hat{b}$ | | | | | | |
| E[Return] | 0.790*** | (0.01) | 0.599*** | (0.01) | 0.614*** | (0.01) |
| SD[Return] | -0.267*** | (0.01) | -0.179*** | (0.02) | -0.176*** | (0.02) |
| Rating | | | -0.520*** | (0.01) | -0.519*** | (0.01) |
| Loan duration: 36 months (ref.) | | | | | | |
| 60 months | | | -1.067*** | (0.03) | -1.045*** | (0.03) |
| ln(Amount) | | | -0.512*** | (0.01) | -0.523*** | (0.01) |
| Description | | | 0.201*** | (0.01) | 0.198*** | (0.01) |
| Offered interest rate | | | 0.405*** | (0.01) | 0.400*** | (0.01) |
| Loan purpose: consumer loan (ref.) | | | | | | |
| business loan | | | 0.095*** | (0.02) | 0.110*** | (0.02) |
| Employment: employed or retired (ref.) | | | | | | |
| self-employed | | | 0.354*** | (0.01) | 0.350*** | (0.01) |
| Age | | | -0.006*** | (0.00) | -0.006*** | (0.00) |
| Financial burden: low (ref.) | | | | | | |
| moderate | | | 0.396*** | (0.02) | 0.407*** | (0.02) |
| substantial | | | 0.541*** | (0.02) | 0.554*** | (0.02) |
| high | | | 0.618*** | (0.03) | 0.624*** | (0.03) |
| Borrower gender: male (ref.) | | | | | | |
| female | | | -0.096*** | (0.01) | -0.094*** | (0.01) |
| $\hat{\sigma}_{\beta}$ | | | | | | |
| E[Return] | 0.528*** | (0.01) | 0.544*** | (0.01) | 0.533*** | (0.01) |
| SD[Return] | 0.479*** | (0.01) | 0.195*** | (0.01) | 0.199*** | (0.01) |
| Rating | | | 0.188*** | (0.01) | 0.198*** | (0.01) |
| Loan duration: 36 months (ref.) | | | | | | |
| 60 months | | | 1.404*** | (0.03) | 1.377*** | (0.03) |
| ln(Amount) | | | 0.264*** | (0.02) | 0.251*** | (0.02) |
| Description | | | 0.096*** | (0.02) | 0.064** | (0.03) |
| Offered interest rate | | | 0.054*** | (0.01) | 0.022** | (0.01) |
| Loan purpose: consumer loan (ref.) | | | | | | |
| business loan | | | 0.008 | (0.04) | 0.013 | (0.04) |
| Employment: employed or retired (ref.) | | | | | | |
| self-employed | | | 0.041* | (0.02) | 0.048** | (0.02) |
| Age | | | 0.000 | (0.00) | 0.000 | (0.00) |
| Financial burden: low (ref.) | | | | | | |
| moderate | | | 0.021 | (0.03) | 0.027 | (0.03) |
| substantial | | | 0.003 | (0.02) | 0.016 | (0.02) |
| high | | | 0.135*** | (0.03) | 0.116*** | (0.03) |
| Borrower gender: male (ref.) | | | | | | |
| female | | | 0.004 | (0.02) | 0.011 | (0.02) |
| $\hat{\gamma}$ | | | | | | |
| E[Return] | | | | | -0.016 | (0.04) |
| SD[Return] | | | | | 0.029 | (0.05) |
| Rating | | | | | -0.020 | (0.03) |
| Loan duration: 36 months (ref.) | | | | | | |
| 60 months | | | | | -0.209** | (0.10) |
| ln(Amount) | | | | | 0.056 | (0.04) |
| Description | | | | | 0.001 | (0.02) |
| Offered interest rate | | | | | 0.028 | (0.04) |
| Loan purpose: consumer loan (ref.) | | | | | | |
| business loan | | | | | -0.139* | (0.08) |
| Employment: employed or retired (ref.) | | | | | | |
| self-employed | | | | | 0.021 | (0.05) |
| Age | | | | | 0.003** | (0.00) |
| Financial burden: low (ref.) | | | | | | |
| moderate | | | | | -0.107 | (0.08) |
| substantial | | | | | -0.145 | (0.14) |
| high | | | | | -0.102 | (0.09) |
| Borrower gender: male (ref.) | | | | | | |
| female | | | | | 0.016 | (0.05) |
| Log-likelihood | -99629 | | -89021 | | -89013 | |
| N | 931271 | | 931271 | | 931271 | |

* p<0.10, ** p<0.05, *** p<0.01; (ref.) = reference category

# Chapter 5

# Effect of Gender on Access to Credit: Evidence from a German Market for Peer-to-Peer Lending

*Joint work with Dorothea Schäfer*

***Abstract***: Studies of peer-to-peer lending in the USA find that female borrowers have better chances of getting funds than males. Is differential treatment of borrowers of different sexes a common feature of peer-to-peer lending markets or is it subject to specific business models, ways of fixing loan contracts and even national financial systems? We aim at answering this question by providing evidence on loan procurement at the largest German peer-to-peer lending platform *Smava.de*. Our results show that gender does not affect individual borrower's chances of funding success on this platform, *ceteris paribus*. Hence, gender discrimination seems to be a platform-specific phenomenon rather than a common attribute of this innovative form of credit markets.

***JEL***: G21, J16
***Keywords***: gender, access to credit, peer-to-peer lending

## 5.1 Introduction

One of the more notable innovations in the financial services industry is the emergence of a new type of credit market known as peer-to-peer (thereafter P2P) lending. P2P lending is carried out directly between borrowers and lenders without intermediation of a traditional credit institution. Moreover, borrower-lender interactions are conducted anonymously via internet-based market places (also called platforms). Currently, more than 30 P2P lending platforms with different business models and loan procurement mechanisms exist in various countries. With $ 1 Billion of outstanding loans, P2P lending is still a niche segment compared to the size of traditional credit market.[1] Nevertheless, it is attracting a growing number of market participants. For borrowers, P2P lending provides an additional source of funds outside the banking system. Lenders in turn obtain access to a new investment instrument. The awareness of this phenomenon grows not only among the general public but also among financial industry professionals and scholars.[2]

For scholars, P2P lending presents a unique framework for studying various aspects of individuals' financial behavior in a real-life setting. One of the central research questions of recent studies is whether personal characteristics of loan applicants such as race, gender and physical looks affect their chances of getting funds at P2P credit (Ravina, 2007; Pope and Sydnor, 2008; Duarte and Young, 2009). Using the data Prosper.com – the largest P2P lending platform in the USA – these studies show that women are more likely to get funds on the platform than men. This finding stands out from the evidence provided by literature investigating gender discrimination in the traditional credit markets. According to this literature, there is either discrimination against female borrowers or no gender discrimination (Peterson, 1981; Holtz-Eakin et al., 1994; Blanchflower and Oswald, 1998; Blanchflower et al., 2003; Cavalluzzo et al., 2002; Alesina et al., 2009; Muravyev et al., 2009).

Furthermore, current P2P lending market is very heterogenous. Existing platforms employ different business models and mechanisms of procurement and operate in different financial systems and cultural environments. Against this background, a justified question is whether evidence from *Prosper* can be generalized for all P2P lending platforms.

The present study contributes to answering this question by providing evidence on the treatment of male and female loan applicants at a P2P platform that differs from Prosper in several important ways. The platform considered is *Smava* and is the largest market place for P2P lending in Germany. In contrast to Prosper, loans at *Smava* are not auctioned but procured on a "take-it-or-leave-it" basis. For instance, loan conditions are set by loan applicants while lenders are the takers of these conditions. Furthermore, a loan applicant at the German platform can get a loan even when the requested sum is not completely funded. At Prosper, only individuals who succeed to raise 100% of the requested sum can get a loan. The next distinguishing feature of *Smava* is the existence of an interior insurance system that protects lenders from total losses. Finally, *Smava* is operating in a bank-based financial system and, thus, matches individuals (borrowers and lenders) who have primarily gained their financial experience in this financial system. Given the uniqueness of the German

[1] Deutscher Bundestag: Kleine Anfrage zum Thema "Private Kreditvergabe im Internet", Drucksache 17/1832.

[2] See Meyer (2009), FTD (2009), Sviokla (2009), Kim (2009), Ravina (2007), Pope and Sydnor (2008), Duarte and Young (2009).

platform, it is an open question whether treatment of borrowers is similar to that observed at Prosper.

The goal of the study is to find out whether males and females have different chances of getting funds at *Smava*. Compared to existing papers on the determinants of funding success at P2P credit markets, our study has two novel features. Firstly, we employ three different indicators of funding success and examine whether results depend on the choice of indicator. Our first indicator of funding success is that a loan applicant manages to raise 100% of the desired amount. The second indicator is that at least 25% of the requested amount is provided. The 25%-percent cutoff is chosen because platform returns the raised money back to lenders when less than 25% is raised. The third indicator of funding success is that a loan request managed to attract at least one lender regardless of the amount offered by the lender.

The second distinguishing feature of our study, compared to the analysis based on the Prosper-data, is the accuracy of identification of applicants' gender. At Prosper, applicants are not obliged to reveal their gender and many do not do so. To infer applicants' gender, previous studies relied on pictures uploaded by applicants at the platform. Yet, only 40% of applicants provided a picture showing people. Even assuming that the pictures truthfully show the actual applicants (and not someone else), researchers obtained information about gender only for some applicants. An analysis of how lenders treat loan applicants of different gender that is based on a sub-sample of applicants with pictures may yield biased evidence due to self-selection of individuals into those who provide pictures and those who do not. The issue of this problem is that lenders may obtain more accurate information about applicants' gender from verbal descriptions provided by applicants. To our knowledge, this information is not taken into account in the existing studies. An analysis based on the *Smava*-data is free of this problem: At the German platform, loan applicants are obliged to reveal their gender, which is information pubically observable to both lenders and researchers. This feature enables an accurate measurement of the effect of gender on the funding success.

We test the effect of applicants' gender on the probability of funding success by means of a multivariate regression analysis. Our results show that gender has no significant effect on funding success. Lenders seem to be equally willing to fund male and female applicants, *ceteris paribus*. This finding holds for different indicators of funding success and a variety of robustness tests. Thus, we are confident that the obtained results reflect the true state rather than being an artifact of a specific estimation technique. All in all, the result of positive discrimination obtained for the US-American platform could not be confirmed with the German data. At *Smava*, access to credit appears to be equally likely for both genders. Therefore we cannot support the claim that gender discrimination is a common feature of P2P lending markets.

The remainder of the paper is organized as follows. The next section provides an overview of the lending mechanism at *Smava* and describes the data. In section 3 we formulate the research hypothesis and describe the test methodology. Section 4 describes the results of the multivariate probit regression. In section 5, we offer a number of robustness checks. The last section concludes by suggesting some explanations of why our results differ from that obtained for Prosper.

## 5.2 Data

### 5.2.1 Borrowing at *Smava*

Peer-to-peer lending means direct lending and borrowing between individuals ("peers") without intermediation of a traditional financial institution. Historical forms of peer-to-peer lending include borrowing from friends, family members or business partners. Recent advances in the Internet-based technologies enabled lending transactions to be carried out at online marketplaces ("platforms") where people who need money are linked to those who are willing to lend money. The first online platform for peer-to-peer lending, *Zopa,* was founded in 2005 in the UK.

Data used in this study are collected from the largest peer-to-peer lending platform in Germany – *Smava*. The platform was launched in March 2007 and specializes in facilitating loans between private individuals. All loans are fixed rate annuities paid back in fixed monthly payments. During the observation period spanning 3 years – from March 2007 to March 2010 – the platform procured more that 3 thousands loans in total volume of € 25 million. The majority of loans are typical consumer loans. Small business loans are also procured and make about a quarter of all loans. As of March 2010, 3,401 loan applicants and more than 5,000 lenders were registered on the platform.

***Loan applications.*** During the observation period, 4,144 loan applications were posted at the platform. The number of applications showed a growing trend since the start of the platform (Figure 5.1). Loan applications may only be posted on the platform by private persons who comply with a number of requirements. Firstly, applicants must be at least 18 years old and have a personal monthly income of at least € 1,000. Secondly, only those whose individual financial burden does not exceed 67 % are eligible to borrow at the platform. Financial burden is defined as a ratio of monthly payments that the applying individual must make on all outstanding debts (including the loans taken at *Smava*) to the personal monthly disposable income. Mortgage payments are treated as expenditures and subtracted from the disposable income. Neither income of other household members nor household savings are taken into account. Depending on the obtained ratio, applicants are rated on a scale from 1 (low financial burden) to 4 (high financial burden), as described in Table 5.3. Furthermore, the platform accepts only applicants with Schufa-rating grades ranging from A to H. Schufa-rating is assigned to individuals by the German national credit bureau and measures individuals' creditworthiness on a 12-point scale from A (the best) to M (the worst). Each rating grade corresponds to an estimate of the probability that an individual defaults on his/her obligations (see Table 5.2). Applicants' identity is verified via the *postident* procedure: Each prospective applicant has to provide officials of the Deutsche Post (German Postal Office) documents that prove his or her identity and address.[3] Compliance with the aforementioned requirements is verified by the platform based on the income statement and the bank account statements that applicants are obliged to send to the platform.

After a successful verification, an accepted applicant posts a loan application where he/she specifies the desired loan amount and the loan terms. The specified loan terms include loan duration and nominal annual interest rate that the applicant is willing to pay. According to the rules imposed by the platform, applicants may not request less than € 500 or more than € 50,000; loan duration may be either 36 or 60 months; and the interest rate has to be between 2 and 18 %. A loan application can be seen as a "take-it-or-leave-it" offer to lenders, because lenders cannot negotiate the terms set by the applicant. However, lenders can refrain from lending if they consider the offer terms unsatisfactory.

Apart from the loan terms, applications also contain some personal information about loan applicants which can be subdivided into "hard" and "soft" information. Hard information includes data that applicants are obliged to provide. These data include age, gender, place of residence, occupation, Schufa-rating, financial burden and, if applicable, past payment history at *Smava*. This information is displayed in a standardized way in each application. Additionally, applicants may (but are not obliged to) provide "soft" information such as, for example, a description of the loan purpose, details of current employment, and family status. Applicants may also upload a picture. In contrast to Prosper, only a negligibly small fraction of loan applicants at *Smava* use this option and provide a photograph. All information provided in a loan application is made public and can be seen by lenders and all other users of the platform.

***Funding.*** Lenders may fund a loan during the 14 days following the moment that a loan application is posted. To conduct a lending transaction, a lender submits electronic offer specifying the amount he/she wants to lend. A single lender usually provides only a fraction of the amount requested by an applicant. By limiting the amount given to a single borrower, lenders try to control the counterparty risk exposure. It takes usually several lenders to fund a single loan. The number ranges between 1 and 73. On average, each loan is funded by 15 lenders. According to the rules set by the platform, the amount invested in one loan can be 250 Euro at minimum and 25,000 Euro at maximum and has to be a multiple of 250. By submitting an offer, lenders "sign" a binding contract and commit to providing the specified

[3]The *postindent* procedure is a standard procedure used in Germany by institutions and firms to verify the identity of prospective clients.

amount of money at terms set in the application. An important peculiarity of *Smava* is that, in contrast to many other peer-to-peer lending sites, loans are *not* auctioned. Lenders cannot underbid offers of other lenders by offering a lower interest rate.

Not every loan applicant manages to raise the desired amount of money. Table 5.1 describes distribution of loan applications by funding success. The fraction of fully funded loans makes 81% of all loan applications.[4]. Remarkably, the fraction of successful applications is somewhat higher for females than males. In contrast to *Prosper*, borrowers at *Smava* are allowed to take the raised amount even if it is smaller than the initially requested amount. The raised money is not paid out only if the raised amount makes less than 25% of the requested sum. In this case, the raised money (if any raised) is returned to lenders. An applicant can post his application again, eventually, specifying different loan terms. Loan applicants are charged by the platform with a fee only when at least 25% of the desired sum is raised and the loan applicant agrees to borrow the raised sum. Depending on the amount of obtained loan, the fee is between 2 and 2.5% of the amount obtained.

***Borrowers' liability.*** Loans procured at the platform are neither secured by collateral nor guaranteed by third parties. Nevertheless borrowers have full liability. If a borrower remains in arrears for six weeks, the claims of lenders on the outstanding loan amount are sold to a collections agency. The agency pays lenders a fee equal 15 to 20 % of the outstanding debt. By buying the claims, the agency acquires the legal right to take a hold of the debtor's total assets to recover the debt. In addition, delinquent borrowers get a negative report in their Schufa credit profile. Both instruments – unlimited liability and creditworthiness downgrade – should have a disciplining effect on borrowers.

***Interior insurance of invested capital.*** In addition to the partial recovery of invested capital through sale of delinquent loans to a collections agency, a further part of the capital can be recovered though an interior insurance employed by the platform. This insurance is accomplished by assigning lenders into groups so that individual risks are shared among the members of one group. Specifically, all lenders who financed loans of the same duration and Schufa-Rating belong to the same group. For example, lenders who granted loans to borrowers with rating "A" for 60 months constitute one group. Due to existence of 8 rating classes and 2 duration types, there are a total of 16 groups. Monthly principal payments received by lenders of the same group are pooled together and each lender gets an amount proportional to his stake in the pool. Each lender's stake is equal to the monthly principal payment stipulated in the loan contract between the lender and the respective borrower. When a borrower fails to pay, the size of the pool decreases by the amount of the missed monthly payment and the remainder is divided among the lenders of the group proportional to their stakes. In effect, all lenders of one group – including those who actually invested in the loan in arrears and those whose borrowers paid on time – get a fraction of the stipulated

[4]This fraction is very high when compared to the 9%-funding rate reported for *Prosper*

monthly payment. This faction is called the *recovery rate*. Table 5.4 report the recovery rates observed at the platform in the past. Interest payments are exempted from the pooling mechanism so that lenders get 100% of the stipulated monthly interest payment if their borrowers pay on time and get 0 otherwise.

### 5.2.2 The Data Set

Our data set includes information on all loan applications posted at the platform from March 2007 to March 2010. A total of 3,401 individuals applied for loans. Females account for 935 (27%) and males account for 2,466 (73%) of loan applicants. The total number of applications is 4,146: 1,114 (27%) applications posted by females and 3,032 (73%) posted by males. The total number of applications exceeds the number of applicants, because each individual may apply for multiple loans or resubmit an application once it is turned down. The list of variables, with definitions, is given in Table 5.5. Summary statistics of the variables by applicants' gender are summarized in Table 5.6. There are some differences between applications of males and females. Firstly, females request, on average, smaller loans than males. Secondly, females offer to pay, on average, 0.3 percent higher interest rates than males. There are also some gender differences in applicants' personal characteristics. For instance, female applicants are on average 4 years older than males. Further, females are less numerous than males among free-lancers, managing partners, but more numerous in the group of retirees. Figure 5.2 plots distributions of applications by loan purpose. The observed gender differences correspond with popular gender stereotypes: Males prevail in the groups related to business, electronics and cars, while females dominate in categories such as health care, family, housekeeping, health care and education but also among those specifying no purpose.

## 5.3 Research Hypothesis and Test Methodology

The credit market studied in this paper has two types of participants: loan applicants indexed with $j$ and lenders indexed with $i$. Loan applicants specify the desired loan amount $L_j$, duration $D_j$ and nominal annual interest rate $I_j$ they are willing to pay. The desired loan amount of applicant $j$ is funded if there are at least $N$ lenders at the market willing to provide funds such that $\sum_{i=1}^{N} L_i = L_j$. Lenders' willingness to provide funds to applicant $j$ depends on their expectations regarding the return to this investment. Return from a loan is determined by the loan's nominal interest rate $I_j$, duration $D_j$, amount $L_j$ and loan applicant's probability of default $p_j$. Lenders do not observe $p_j$. However, they may infer $p_j$ from loan applicants' observable characteristics captured in vector $\mathbf{X}$. Assume that, given $\mathbf{X}$, all lenders expect to get the same return.

Our research question is whether male and female loan applicants have equal chances of getting funds given that they offer equal loan terms and are similar with respect to all observable characteristics. Gender can affect applicants' chances of funding success only when lenders discriminate against loan applicants of a particular sex. Discrimination in a credit market may emerge because of two reasons. On the one hand, imperfect information about borrowers' quality may lead to statistical discrimination (Phelps, 1972; Arrow, 1973). For instance, because lenders do not observe applicants' probability of default, they may use applicants' gender as a screening device if they believe that gender is correlated with the probability of default. In this case, two applicants who are identical in all observable characteristics except gender will be assigned different probabilities of default. Let the probability of default of a female borrower, as perceived by lenders, be $p$, and the probability of default of a male borrower be $p+\delta$. For profit maximizing lenders, $\delta \neq 0$ provides an incentive to charge a higher risk premium from a borrower with a higher probability of default, *ceteris paribus*. On the other hand, Becker (1957) argues that even in the absence of statistical discrimination, lenders may have taste-based preference against applicants of a particular sex due to distaste or prejudice. In this case, lenders will require an additional compensation for lending to unfavored applicants even when these applicants are not actually riskier than others. All in all, both types of discrimination imply that loan applicants of a particular gender have to pay a higher price for credit than other applicants, *ceteris paribus*. Respectively, loan applicants of different gender who offer the same loan terms have different probability of getting credit, *ceteris paribus*. Hence, the hypothesis that we test reads:

*If loan applicants of different gender offer the same loan terms and are similar with respect to other observable characteristics, the applicant from the discriminated gender group will face a lower probability of funding success.*

The remainder of the paper is devoted to the test of this hypothesis. The test relies on a reduced form equation

$$Pr(Funding_j = 1) = \Phi(\beta_0 + \beta_1 Male_j + \beta_2 I_j + \beta_3 D_j + \beta_4 L_j + \boldsymbol{\beta}_5 \mathbf{X}_j), \qquad (5.1)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, and $\mathbf{X}_j$ is a vector of variables capturing all observable characteristics of loan applicants and loan terms. The model's coefficients are estimated by means of a probit regression. The dependent variable in the regression equation is a binary variable equal 1 if a loan is successfully funded and 0 otherwise. We use three different indicators of funding success. According to the first indicator, only loan requests that were completely funded are considered as funding success. Under the second indicator, cases where applicants raised at least 25% of the requested amount are considered to be funding success. Under the third indicator, all loan requests that received at least one offer from lenders (regardless of the offered amount) are considered as successful.

The main variable of interest is the dummy variable *Male* equal 1 if loan applicant is male and 0 if female. The effect of gender is captured in the coefficient $\beta_1$. The estimate of $\beta_1$ shows whether loan applicants' gender has an effect on the probability of funding success. In particular, $\hat{\beta}_1 > 0$ ($\hat{\beta}_1 < 0$) would indicate that males have better (worse) chances of getting funds than females.[5]

## 5.4 Estimation Results

Table 5.7 reports the estimated marginal effects of the explanatory variables. The first two columns of the table report results for the case when the dependent variable equals 1 if a loan request is funded completely and 0 otherwise. Column (1) summarizes the results of a baseline specification of Equation 5.1 that includes a dummy variable *Male*, a set of variables capturing loan terms, a set of dummy variables indicating applicants' Schufa-rating scores, and a set of dummy variable capturing the time effects (quarterly dummies). Column (2) reports results for an extended specification of the regression equation that includes all observed attributes of loan applicants, loan terms and time effects. Both model specifications predict a strong positive relationship between the offered interest rate and the probability of funding. Loans with duration of 60 months have lower probability of being funded compared to loans with a shorter duration of 36 months. The requested loan amount has a negative effect on the probability of outcome.[6] Apparently, and similar to traditional bank lending, lenders associate longer durations and higher loan amounts with more uncertainty in repayments and therefore require higher premia compared to short-term loans and smaller loan amounts. Altogether, variables representing loan terms seem to be highly predictive of the probability of funding success. In contrast, applicants' gender has no statistically significant effect on the probability of raising the requested sum. This result holds also when we extend the model's specification by including additional control variables (see column (2)). According to the respective values of $Pseudo-R^2$, the extended model describes the variation in the probability of outcome better than the baseline specification. Some of the applicant-specific attributes seem to play a role in the funding success. For instance, we find a positive relationship between the applicant's financial burden and probability of funding success. At first glance, this finding seems counterintuitive.

[5] $\hat{\beta}_1 \neq 0$ would indicate that lenders discriminate against borrowers of a particular sex. The estimation procedure does not however allow identification of the type of discrimination – statistical or taste-based. Identification of the type of discrimination is beyond the scope of this paper.

[6] The variable capturing loan amount is calculated by dividing the loan value measured in Euro by 250. We do this adjustment because applicants may request only amounts that are multiples of 250. Thus, the coefficient of the variable *Amount* should be interpreted as follows: An increase in requested amount by 250 Euro, decreases the probability of funding success by 0.4 percentage points.

Yet, availability of other debts (mostly bank loans) may be viewed by lenders as an indicator of good quality of a borrower (banks would not have lent money otherwise). In these circumstances, additional indebtedness of loan applicants is more appealing to lenders than absence of any information about individuals' credit histories. Other control variables seem to have a limited effect on the probability of funding success.

Columns (3) and (4) of Table 5.7 report the results for the case when the dependent variable equals 1 if at least to 25% of the requested loan amount are funded and 0 otherwise. As previously, the baseline equation includes only few explanatory variables and the second one includes all observable characteristics. Similar to the previous specification of the dependent variable, the effect of gender is found to be insignificant, while loan terms and some of individual characteristics remain important determinants of the probability of funding.

Finally, estimation results for the case when the dependent variable is equal 1 if at least some funds are offered to an applicant are reported in column (5) and (6). For the baseline specification of the regression equation, the effect of gender is again statistically insignificant. For the extended specification, the effect of gender is statistically significant at 10% level. The estimated coefficient of variable *Male* suggests that males are by 1.2 percentage points less likely to get at least some offers from lenders than females. In relation to the overall fraction of 92% of loan applications with at least one offer, a difference of 1.2 percentage points means only a 1% decrease in the probability of success. Hence, the magnitude of the effect is very small to claim that gender makes a difference.

## 5.5 Robustness Checks

### 5.5.1 Does Gender Effect Vary With Rating and Interest Rate?

According to Equation 5.1, the effect of gender is captured in a single coefficient $\beta_1$. Such model specification restricts the effect of gender to be the same for all values of other explanatory variables. Yet, we cannot exclude the possibility that lenders' attitudes towards borrowers of particular sex depend on loan terms. For instance, lenders may be indifferent between male and female applicants as long as the offered interest rate is either very low or very high. They may also be equally willing to lend to male and female borrowers if they have the best rating scores, but discriminate against borrowers of a particular sex if the rating is poor. In both cases, the effect of gender should vary across different levels of interest rate and across rating grades. To allow for a varying gender effect, we extend Equation 5.1 by including interactions of the dummy variable $Male$ with the continuous variable $Interest\,rate$ and with the set of dummy variables indicating borrowers' rating.

Results of the estimation are reported in Table 5.8. Column 1 of the table shows the results for the case when funding success is defined as a loan being fully funded. Here, the estimates of coefficients of the interaction terms are statistically insignificant, meaning that gender has no effect on the funding success regardless of the level of interest rate and applicants' rating score. Column 2 of the table reports coefficient estimates for the case when funding success is defined as a loan being funded at least to 25%. In this case, the effect of gender is also insignificant across all levels of interest rate and rating. The third column of the table reports the results for the case when all loan applications that received at least one offer from lenders are considered as successful. According to the coefficient estimates, the level of offered interest rate and applicants' rating seem to have some effect on gender differences in the probability of getting at least one offer from lenders. For instance, male applicants are predicted to be less likely to get an offer than female applicants as the interest rate increases. However, males with Schufa-Rating grade "B" and "D" seem to have somewhat higher probability of success than females with the same rating grades. All in all, we can confirm our previous findings that gender does not affect the probability of loan being funded completely or at least to 25%. It is only the probability to get at least one offer from lenders that depends to some extent on the applicant's gender. However, the direction of the effect may change depending on the individual combination of the characteristics of a loan applicant.

### 5.5.2 Endogenous Regressors

A potential concern with equation 5.1 is that two variables – the offered interest rate and the loan amount – are endogenous. Borrowers can influence own chances of funding success by offering the appropriate loan terms. For instance, higher loan rates and lower loan amounts are associated with higher probability of funding, *ceteris paribus*. Borrowers who wish to increase their chances for success might offer higher interest rates or request lower loan amounts. In this circumstance, the loan rate and the loan amount are not exogenous factors. Rather there emerges a reciprocal causation (or simultaneity) between these factors and the probability of funding success. The problem of reciprocal causation is widely discussed in the statistical literature (Heckman, 1978; Amemiya, 1978, 1979). In the presence of simultaneity, the standard estimation method applied earlier in this paper may produce biased estimates. This bias can be corrected by using a two-stage estimation procedure whereby endogenous variables in Equation 5.1 are replaced with exogenous instruments.[7] For the sake of brevity, we conduct the two-state estimation procedure only for the case when funding success is defined as a loan being fully funded.

In the first stage, we estimate two auxiliary regressions. The first one is an OLS regression of the requested loan amount, divided by 250, on a set of exogenous variables. This set includes loan applicants' gender, Schufa-rating, financial burden, employment status, age,

[7]The estimation is conducted according to the minimum-chi-squared estimation method developed by Newey (1987).

place of residence, loan maturity, loan purpose, length of description and time-dummies. The second auxiliary OLS regression estimates the effect of the same set of exogenous variables on the offered interest rate.[8] The estimation results of the two auxiliary regressions are reported in Panel *A* of Table 5.9.

After the two auxiliary regressions are estimated, the fitted values of interest rate and loan amount can serve as instruments for the endogenous variables in Equation 5.1. In order to fulfill the identification conditions, some of the exogenous variables entering the auxiliary regressions must be excluded from the main equation. We suggest excluding borrowers' employment status and place of residence. Borrowers' employment status is clearly one of the factors that affect borrower riskiness. Compare, for example, a civil servant whose income is quite safe with a self-employed person whose income may be very uncertain. Hence, certain jobs should be associated with higher interest rate as lenders require higher risk premia from riskier jobs. Indeed, results from the auxiliary regression of interest rate confirm this conjecture: Civil servants offer on average lower interest rates than individuals with other employment statuses, whereas sole proprietors and retirees offer the highest interest rates among all loan applicants. While being relevant for the level of interest rate, employment status should not affect the probability of getting a loan. As soon as job-related risks are compensated with an appropriate risk premium, lenders should be indifferent with respect to borrowers' employment status. Because lenders themselves have different employment statuses, their individual taste-based preferences in favor (or against) certain jobs should not systematically affect borrowers' probability of funding success. Indeed, when looking at the estimation results in Table 5.7, borrower employment status has barely an effect on the probability of success. The negative effect of the indicator variable *Retired* probably captures the effect of age and the associated mortality risks, rather than the retirement status per se.

The exclusion of variables indicating place of residence is justified by different costs of living across federal states. Significant discrepancies in these costs imply that loan applicants from "more expensive" lands should request higher loan amounts for the same purpose than applicants from "less expensive" lands. At the same time, place of residence

[8]One might think that loan amount should also be taken into account as a determinant of loan interest rate. In the traditional bank lending, dependence of interest rate on loan amount is driven by the fact that marginal costs of providing credit vary with loan amount. In contrast, in the context of P2P, the costs faced by each individual lender are not necessarily related to the total amount requested by a loan applicant. For instance, due to a fixed fee of 4 Euro paid by a lender each time he/she lends money, the costs of lending are a function of the amount lent and not on the amount of requested by the applicant. As described earlier, each lender usually lends only a fraction of the total requested sum. Hence, in the considered credit market loan amount is not expected to affect the loan interest rate. To prove that this is indeed the case, we regress the interest rates on all observable loan- and borrower-specific characteristics and a set of dummy-variables indicating deciles of the requested loan amount. The flexible functional form of loan amount should allow us to capture non-linear relationship between interest rate and amount if such exist. The results of OLS estimation show however that the requested amount has no statistically significant effect on the offered interest rate. Hence, we can argue that the requested loan amount must not enter the equation describing the offered interest rate.

should not affect loan applicants' chances of funding, because lenders live in various federal states and altogether cannot systematically affect the results of outcomes in favor or against some of the states. Results of the auxiliary regression of loan amount on applicants' place of residence and other observable characteristics show in fact, that four federal states – Bavaria, Bremen, Schleswig-Holstein and Saxony – are associated with higher loan amounts as compared to Berlin. In contrast, regression results in Table 5.7 revealed no systematic relationship between federal state and the probability of funding success.

The estimation results of the second-stage equation are reported in Panel *B* of Table 5.9. At the bottom of the table is a Wald test for the exogeneity of the two instrumented variables $Loan\,amount$ and $Interest\,rate$. The test statistic is not significant. Hence, the null hypothesis of exogeneity cannot be rejected. Thus, the initial estimation of Equation 5.1 by means of a simple probit regression is also appropriate and yields consistent estimates. Moreover, the coefficient estimate for variable $Male$ in the two-stage regression is also statistically insignificant. Hence, our robustness checks confirm the earlier obtained result that applicants' gender has no influence on the probability of getting a loan, *ceteris paribus*.

### 5.5.3 Discrepancies in Observable Characteristics

Parameter estimates obtained in the first-stage regression (Panel *A* of Table 5.9) show that male applicants offer lower interest rates and at the same time request higher loan amounts than female applicants. Moreover, as revealed by descriptive statistics in Table 5.6, apart from the requested loan amount and interest rate, significant gender differences also exist with respect to applicants' age and employment status. Substantial dissimilarities between the two gender groups with respect to observable characteristics may render the estimates of the *ceteris paribus* effects of gender inconsistent. In order to test the robustness of our results with respect to this sample problem, we conduct Heckman's difference-in-difference matching estimation using kernel matching to determine the weights of matched observations (Heckman et al., 1998; Smith and Todd, 2005). The goal is to estimate the effect of gender using a sample of matched individuals, that is, loan applicants who differ only with respect to gender but are similar with respect to all other characteristics.

Similarity of loan applicants is determined based on their propensity score. A propensity score presents the probability that a loan applicant is male given all observable characteristics of the applicant and the application. This probability is estimated by means of a logit regression whereby an indicator variable $Male$ is regressed on all observable variables. Distributions of male and female applicants by estimated propensity scores are plotted in Figure 5.3. The shapes of the distributions are very similar. Hence, there is a good chance that for every loan applicant we find "twins" of the opposite sex. Indeed, only 25 males happen to fall outside the common support which means that they remain unmatched as there are no females with similar propensity scores. These 25 loan applicants are excluded from the further analysis. Observations that are on the common support are then used to calculate the matching estimator of the effect of gender on the probability of funding success. According to the results, difference in the probability of funding success between male and females equals -0.003 and is statistically not significant.[9] Thus, the results of the robustness check confirm the results obtained in the initial estimation procedure.

## 5.6 Conclusions

The question of whether evidence obtained from *Prosper* can be generalized to other P2P platforms motivated us to analyze the role of gender at the largest German platform *Smava*. The results of our analysis do not reveal any significant gender differences in the probability of funding success when all observable characteristics of loan applicants and loan terms are taken into account. The obtained result is robust to different definitions of funding success and a number of robustness checks. Therefore, we conclude that no gender discrimination takes place on the German platform.

There are three possible explanations of why our results differ from the evidence obtained from the *Prosper*-data. Firstly, the results obtained for *Prosper* may be driven by the discrepancies between the information about applicants' gender that is observable to lenders and the information analyzed by researchers. Secondly, we may have found no discrimination at *Smava* because the platform is relatively young and lenders do not have enough *ex-post* evidence on borrowers' payment behavior. As documented by recent literature, market experience and especially loss experience exerts significant influence on the behavior of market participants (Braga et al., 2009). Hence, it is expected that lenders will adjust their behavior if they learn from updated information that borrowers' gender affects payment behavior. The same consideration applies to the US-American platform. Although it was founded two years earlier than the German platform, the majority of procured loans have not yet matured. This motivates further investigation of lending behavior at the P2P markets as they become more mature. Finally, divergent results obtained for the US-American and the German platform might be determined by the specifics of the platforms' procurement mechanism or the fact that they operate in different financial systems. However, because all existing studies, including the present one, are confined to a single P2P platform, no conclusions regarding the role of these factors can be derived. It is a goal of future research to conduct a comparative analysis of different P2P platforms in order to identify implications of different procurement mechanisms and environmental factors for the behavior of lenders and borrowers.

[9] We test the balancing of variables between the matched male and females using the method of Rosenbaum and Rubin (1985). According to the test results, the differences between the two sub-sample are statistically not significant.

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# Appendix A

Figure 5.1: Loan applications at *Smava*

This graph plots the number of loan applications posted and the total amount requested by the applicants each month

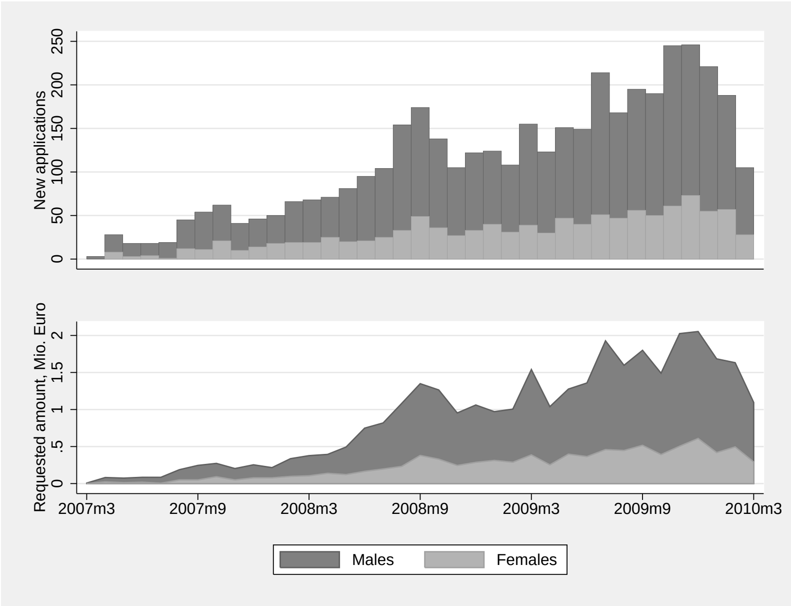


Figure 5.2: Distribution of applications by loan purpose

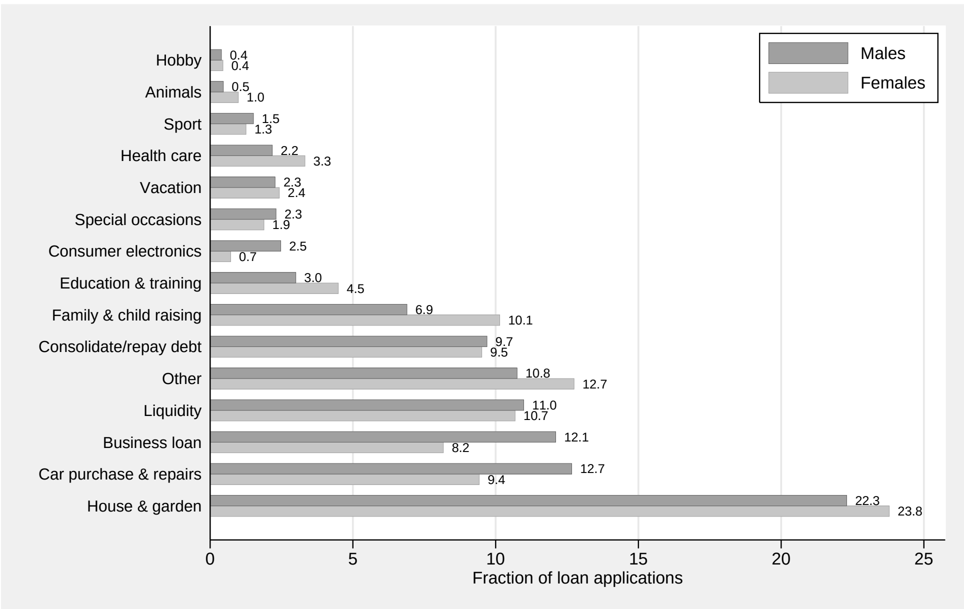

Figure 5.3: Distribution of male and female applicants by propensity score

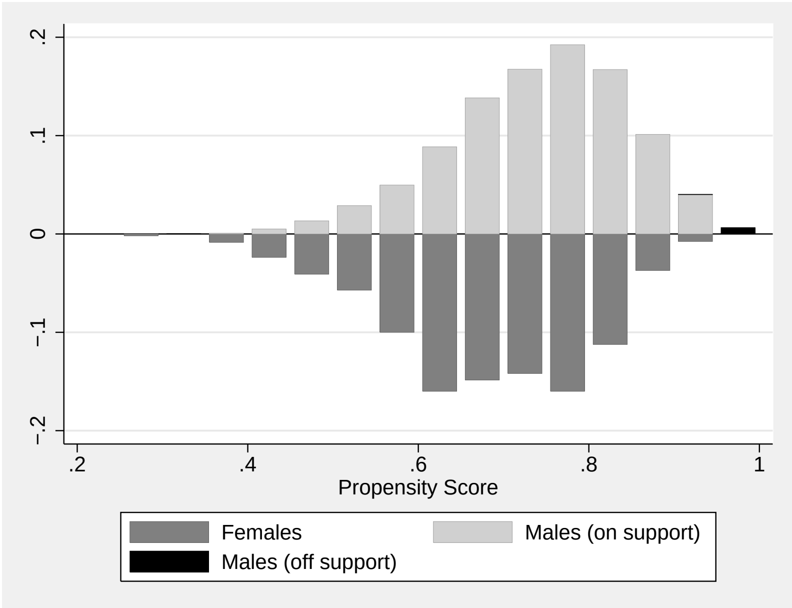


Table 5.1: Distribution of applications by funding success

| | Fraction of applications, in % | | |
|---|---|---|---|
| **Funded amount in % of requested amount** | **by all applicants** N = 4,146 | **by females** N = 1,114 | **by males** N = 3,032 |
| 0 % raised (no bids submitted) | 7.72 | 5.75 | 8.44 |
| > 0 but < 25 % raised | 5.40 | 5.39 | 5.41 |
| ≥ 25 but < 100 % raised | 5.96 | 5.75 | 6.04 |
| 100 % raised | 80.92 | 83.12 | 80.11 |
| Total | 100.00 | 100.00 | 100.00 |

Table 5.2: Schufa rating scores

This table shows the Schufa-Rating scores with respective estimates of the probability of an applicant's default. The rating is assigned to individuals by the German national credit bureau SCHUFA.

| Rating score | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| Probability of default, in % | 1.38 | 2.46 | 3.56 | 4.41 | 5.57 | 7.16 | 10.72 | 15.02 |

Table 5.3: Measure of financial burden

| Financial burden | Fraction of monthly income utilized to serve outstanding debts |
|---|---|
| low | 0 - 20% |
| moderate | 20 - 40% |
| substantial | 40 - 60% |
| high | 60 - 67% |

Table 5.4: Recovery rates

This table reports average historical recovery rates (in % of the invested sum) in the groups of lenders. Source: http://www.smava.de.

| **Schufa-Rating** | | | | | | | |
|---|---|---|---|---|---|---|---|
| A | B | C | D | E | F | G | H |
| **Loans with duration 36 months** | | | | | | | |
| 97.7 | 95.1 | 97.6 | 95.0 | 94.0 | 91.0 | 88.8 | 86.2 |
| **Loans with duration 60 months** | | | | | | | |
| 99.2 | 97.9 | 98.3 | 93.0 | 94.9 | 94.7 | 87.3 | 85.7 |

Table 5.5: Variables and definitions

| Variable name | Description |
|---|---|
| *Interest rate* | Nominal interest rate offered by applicant in the application, in % p.a. |
| *Duration: 60 months* | dummy variable equal 1 if loan requested for 60 months and 0 if for 36 months |
| *Loan amount* | Loan amount requested by applicant, in Euro. |
| *Schufa-Rating* | Categorical variable with 8 values corresponding to Schufa-Rating scores (see Table 5.2) |
| *Financial burden* | Categorical variable with 4 values corresponding to the severity of financial burden defined in Table 5.3 |
| *Employment status* | Categorical variable indicating applicants' employment status: Employee, Civil servant, Freelancer, Managing partner, Sole proprietor or Retiree |
| *Age* | Age of applicant in years |
| *Loan purpose* | Categorical variable with 12 values showing loan purpose |
| *Description* | Logarithm of the number of characters in the detailed description of loan purpose and own personality |
| *Place of residence* | Categorical variable one of the 16 federal states where the applicant lives |

Table 5.6: Descriptive statistics

| Variable | Male applicants Mean | Male applicants St.Dev. | Female applicants Mean | Female applicants St.Dev. | t-Test | p-Value |
|---|---|---|---|---|---|---|
| *Interest rate* | 9.78 | 3.45 | 10.15 | 3.44 | -3.06 | 0.00 |
| *Duration: 60 months* | 0.42 | 0.49 | 0.40 | 0.49 | 1.04 | 0.30 |
| *Loan amount* | 8169.94 | 6296.07 | 7475.54 | 5668.68 | 3.23 | 0.00 |
| *Schufa-Rating*: | | | | | | |
| A | 0.16 | 0.36 | 0.14 | 0.35 | 1.29 | 0.20 |
| B | 0.16 | 0.37 | 0.15 | 0.36 | 0.43 | 0.67 |
| C | 0.09 | 0.29 | 0.10 | 0.30 | -0.22 | 0.82 |
| D | 0.10 | 0.30 | 0.10 | 0.29 | 0.46 | 0.65 |
| E | 0.11 | 0.31 | 0.10 | 0.30 | 0.59 | 0.56 |
| F | 0.12 | 0.32 | 0.13 | 0.34 | -1.22 | 0.22 |
| G | 0.16 | 0.37 | 0.16 | 0.37 | -0.12 | 0.91 |
| H | 0.11 | 0.31 | 0.12 | 0.33 | -1.37 | 0.17 |
| *Financial burden*: | | | | | | |
| low | 0.17 | 0.38 | 0.15 | 0.36 | 1.73 | 0.08 |
| moderate | 0.23 | 0.42 | 0.25 | 0.43 | -1.55 | 0.12 |
| substantial | 0.33 | 0.47 | 0.35 | 0.48 | -1.00 | 0.32 |
| high | 0.27 | 0.44 | 0.25 | 0.43 | 1.10 | 0.27 |
| *Employment status*: | | | | | | |
| Employee | 0.52 | 0.50 | 0.54 | 0.50 | -0.93 | 0.35 |
| Civil servant | 0.04 | 0.20 | 0.03 | 0.18 | 1.49 | 0.14 |
| Freelancer | 0.09 | 0.28 | 0.06 | 0.25 | 2.41 | 0.02 |
| Managing partner | 0.06 | 0.22 | 0.03 | 0.15 | 4.02 | 0.00 |
| Sole proprietor | 0.21 | 0.41 | 0.19 | 0.40 | 1.17 | 0.24 |
| Retiree | 0.08 | 0.27 | 0.15 | 0.35 | -5.79 | 0.00 |
| *Age* | 43.21 | 13.02 | 47.02 | 14.81 | -8.04 | 0.00 |
| *Description* | 5.76 | 1.11 | 5.70 | 1.13 | 1.44 | 0.15 |
| *Place of residence*: | | | | | | |
| Baden-Württemberg | 0.14 | 0.35 | 0.11 | 0.31 | 2.66 | 0.01 |
| Bayern | 0.16 | 0.37 | 0.17 | 0.38 | -0.59 | 0.55 |
| Berlin | 0.07 | 0.25 | 0.10 | 0.30 | -3.98 | 0.00 |
| Brandenburg | 0.03 | 0.17 | 0.04 | 0.18 | -1.05 | 0.29 |
| Bremen | 0.01 | 0.09 | 0.01 | 0.08 | 0.34 | 0.73 |
| Hamburg | 0.03 | 0.17 | 0.03 | 0.18 | -0.36 | 0.72 |
| Hessen | 0.09 | 0.28 | 0.09 | 0.28 | -0.02 | 0.98 |
| Mecklenburg-Vorpommern | 0.01 | 0.11 | 0.02 | 0.14 | -1.34 | 0.18 |
| Niedersachsen | 0.09 | 0.28 | 0.07 | 0.26 | 1.90 | 0.06 |
| Nordrhein-Westfalen | 0.20 | 0.40 | 0.19 | 0.39 | 1.06 | 0.29 |
| Rheinland-Pfalz | 0.05 | 0.21 | 0.05 | 0.22 | -0.52 | 0.60 |
| Saarland | 0.01 | 0.10 | 0.01 | 0.08 | 1.01 | 0.31 |
| Sachsen | 0.04 | 0.19 | 0.05 | 0.21 | -0.94 | 0.35 |
| Sachsen-Anhalt | 0.02 | 0.15 | 0.02 | 0.12 | 1.33 | 0.18 |
| Schleswig-Holstein | 0.03 | 0.18 | 0.03 | 0.18 | 0.21 | 0.83 |
| Thüringen | 0.02 | 0.14 | 0.03 | 0.17 | -1.52 | 0.13 |

Table 5.7: Determinants of funding success

This table reports estimated marginal effects and standard errors (in parentheses) after probit regression. Column (1) and (2) report results for equation 5.1 with a dependent variable equal to 1 if a loan application raised 100% of the requested sum, 0 otherwise. Column (3) and (4) report results for the case where the dependent variable is a dummy equal to 1 if a loan was funded at least to 25% and 0 otherwise. Column (5) and (6) report results for the case when the dependent variable is a dummy equal to 1 if a loan application received at least on offer from lenders, and 0 otherwise. ***, ** and * indicate significance at 0.01, 0.05 and 0.1 levels respectively. The number of observations in all specifications is 4,144.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Male* | -0.008 | -0.012 | -0.008 | -0.008 | -0.010 | -0.012* |
| | (0.010) | (0.010) | (0.008) | (0.008) | (0.007) | (0.006) |
| *Interest rate* | 0.063*** | 0.055*** | 0.052*** | 0.043*** | 0.030*** | 0.026*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) |
| *Duration: 60 months* | -0.052*** | -0.064*** | -0.054*** | -0.059*** | -0.028*** | -0.031*** |
| | (0.012) | (0.011) | (0.010) | (0.009) | (0.008) | (0.008) |
| *Loan amount (divided by 250)* | -0.004*** | -0.003*** | -0.002*** | -0.002*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Rating* | | | | | | |
| A (reference category) | | | | | | |
| B | -0.046*** | -0.048*** | -0.026*** | -0.025*** | -0.010** | -0.010** |
| | (0.007) | (0.008) | (0.006) | (0.006) | (0.005) | (0.005) |
| C | -0.067*** | -0.064*** | -0.037*** | -0.035*** | -0.020*** | -0.022*** |
| | (0.010) | (0.010) | (0.009) | (0.009) | (0.009) | (0.009) |
| D | -0.121*** | -0.121*** | -0.097*** | -0.093*** | -0.053*** | -0.050*** |
| | (0.014) | (0.014) | (0.013) | (0.011) | (0.010) | (0.010) |
| E | -0.152*** | -0.146*** | -0.118*** | -0.104*** | -0.083*** | -0.072*** |
| | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.011) |
| F | -0.265*** | -0.262*** | -0.232*** | -0.222*** | -0.137*** | -0.128*** |
| | (0.017) | (0.017) | (0.016) | (0.018) | (0.017) | (0.018) |
| G | -0.403*** | -0.383*** | -0.394*** | -0.365*** | -0.272*** | -0.244*** |
| | (0.018) | (0.019) | (0.019) | (0.020) | (0.025) | (0.023) |
| H | -0.551*** | -0.535*** | -0.554*** | -0.521*** | -0.422*** | -0.377*** |
| | (0.023) | (0.024) | (0.023) | (0.026) | (0.031) | (0.031) |
| *Financial burden* | | | | | | |
| low (reference category) | | | | | | |
| moderate | - | 0.047*** | - | 0.047*** | - | 0.018** |
| | | (0.015) | | (0.013) | | (0.009) |
| substantial | - | 0.081*** | - | 0.084*** | - | 0.035*** |
| | | (0.014) | | (0.013) | | (0.009) |
| high | - | 0.110*** | - | 0.100*** | - | 0.041*** |
| | | (0.015) | | (0.013) | | (0.010) |
| *Employment status* | | | | | | |
| Civil servant (reference category) | | | | | | |
| Employee | - | -0.034* | - | -0.003 | - | -0.007 |
| | | (0.019) | | (0.017) | | (0.012) |
| Free-lancer | - | -0.014 | - | 0.009 | - | -0.012 |
| | | (0.023) | | (0.020) | | (0.016) |
| Managing partner | - | -0.034 | - | 0.015 | - | 0.022 |
| | | (0.027) | | (0.025) | | (0.019) |
| Sole proprietor | - | -0.035 | - | 0.007 | - | -0.005 |
| | | (0.020) | | (0.018) | | (0.014) |
| Retiree | - | -0.073*** | - | -0.025 | - | -0.024 |
| | | (0.026) | | (0.023) | | (0.016) |
| *Age* | - | -0.001* | - | -0.001* | - | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| *Description* | - | 0.031*** | - | 0.010*** | - | 0.010*** |
| | | (0.005) | | (0.004) | | (0.003) |

(continued on the next page)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Loan purpose* | | | | | | |
| House & garden (reference category) | | | | | | |
| Education & training | - | -0.012 | - | 0.017 | - | 0.006 |
| | | (0.022) | | (0.019) | | (0.020) |
| Car purchase & repairs | - | -0.031** | - | -0.013 | - | -0.024** |
| | | (0.015) | | (0.012) | | (0.010) |
| Business loan | - | 0.021 | - | 0.024 | - | 0.028** |
| | | (0.017) | | (0.014) | | (0.012) |
| Family & child raising | - | -0.008 | - | -0.001 | - | -0.009 |
| | | (0.017) | | (0.014) | | (0.013) |
| Special occasions | - | -0.059* | - | -0.029 | - | -0.007 |
| | | (0.034) | | (0.025) | | (0.016) |
| Health care | - | 0.002 | - | 0.031 | - | 0.002 |
| | | (0.023) | | (0.018) | | (0.014) |
| Liquidity | - | 0.008 | - | 0.007 | - | 0.013 |
| | | (0.016) | | (0.013) | | (0.011) |
| Vacation | - | -0.030 | - | -0.046* | - | -0.051** |
| | | (0.031) | | (0.026) | | (0.025) |
| Hobby | - | -0.017 | - | -0.008 | - | -0.084*** |
| | | (0.067) | | (0.028) | | (0.039) |
| Other/Not specified | - | -0.050*** | - | -0.011 | - | -0.012 |
| | | (0.016) | | (0.013) | | (0.010) |
| Sport | - | 0.015 | - | 0.010 | - | 0.004 |
| | | (0.029) | | (0.025) | | (0.013) |
| Animals | - | -0.050 | - | -0.007 | - | -0.022 |
| | | (0.047) | | (0.049) | | (0.042) |
| Consolidate/repay debt | - | -0.015 | - | 0.006 | - | -0.008 |
| | | (0.017) | | (0.013) | | (0.010) |
| Consumer electronics | - | -0.028 | - | -0.008 | - | 0.003 |
| | | (0.024) | | (0.021) | | (0.021) |
| *Place of residence* | | | | | | |
| Berlin (reference category) | | | | | | |
| Baden-Württemberg | - | 0.025 | - | -0.015 | - | -0.005 |
| | | (0.020) | | (0.017) | | (0.013) |
| Bayern | - | 0.017 | - | -0.000 | - | 0.007 |
| | | (0.020) | | (0.017) | | (0.012) |
| Brandenburg | - | 0.004 | - | 0.002 | - | 0.023 |
| | | (0.032) | | (0.021) | | (0.015) |
| Bremen | - | -0.019 | - | -0.020 | - | 0.031 |
| | | (0.074) | | (0.035) | | (0.061) |
| Hamburg | - | 0.072** | - | 0.029 | - | 0.019 |
| | | (0.028) | | (0.024) | | (0.021) |
| Hessen | - | 0.030 | - | -0.003 | - | 0.016 |
| | | (0.022) | | (0.019) | | (0.013) |
| Mecklenburg-Vorpommern | - | 0.047 | - | -0.018 | - | 0.020 |
| | | (0.030) | | (0.024) | | (0.016) |
| Niedersachsen | - | 0.034 | - | -0.004 | - | 0.006 |
| | | (0.022) | | (0.018) | | (0.015) |
| Nordrhein-Westfalen | - | 0.016 | - | -0.014 | - | -0.002 |
| | | (0.019) | | (0.016) | | (0.012) |
| Rheinland-Pfalz | - | 0.024 | - | -0.007 | - | -0.000 |
| | | (0.024) | | (0.020) | | (0.015) |
| Saarland | - | -0.029 | - | -0.087* | - | -0.068 |
| | | (0.052) | | (0.055) | | (0.064) |
| Sachsen | - | 0.004 | - | -0.030 | - | -0.001 |
| | | (0.028) | | (0.024) | | (0.017) |
| Sachsen-Anhalt | - | 0.008 | - | -0.042 | - | -0.036 |
| | | (0.034) | | (0.028) | | (0.028) |
| Schleswig-Holstein | - | 0.063** | - | 0.014 | - | -0.005 |
| | | (0.026) | | (0.023) | | (0.019) |
| Thüringen | - | 0.034 | - | -0.019 | - | -0.004 |
| | | (0.030) | | (0.027) | | (0.018) |
| *Time effects* | Yes | Yes | Yes | Yes | Yes | Yes |
| Pseudo-$R^2$ | 0.466 | 0.515 | 0.529 | 0.581 | 0.557 | 0.609 |

Table 5.8: Determinants of funding success (with interaction terms)

This table reports the estimated coefficients and standard errors (in parentheses) after probit regression. Column (1) reports results for equation with a dependent variable equal 1 if a loan application raised 100% of the requested sum, 0 otherwise. Column (2) reports results for the case when dependent variable is a dummy equal 1 if a loan was funded at least to 25% and 0 otherwise. Column (3) reports results for the case where the dependent variable is a dummy equal 1 if a loan application received at least on offer from lenders, and 0 otherwise. ***, ** and * indicate significance at 0.01, 0.05 and 0.1 levels respectively. The number of observations in all specifications is 4,144.

| | (1) | (2) | (3) |
|---|---|---|---|
| *Male* | -0.488 | -0.038 | 0.381 |
| | (0.628) | (0.703) | (0.830) |
| *Interest rate* | 0.731*** | 0.932*** | 1.039*** |
| | (0.066) | (0.078) | (0.105) |
| *Male* $\times$ *Interest rate* | 0.043 | -0.034 | -0.193* |
| | (0.068) | (0.077) | (0.103) |
| *Rating* | | | |
| A (reference category) | | | |
| B | -1.473*** | -1.247** | -1.877*** |
| | (0.399) | (0.492) | (0.546) |
| C | -2.025*** | -2.513*** | -2.822** |
| | (0.520) | (0.706) | (1.261) |
| D | -2.504*** | -3.062*** | -4.032*** |
| | (0.559) | (0.677) | (0.832) |
| E | -2.648*** | -3.485*** | -3.201*** |
| | (0.562) | (0.711) | (0.870) |
| F | -4.748*** | -5.503*** | -4.098*** |
| | (0.506) | (0.658) | (0.945) |
| G | -5.161*** | -6.695*** | -6.653*** |
| | (0.570) | (0.668) | (0.864) |
| H | -6.703*** | -8.482*** | -8.842*** |
| | (0.673) | (0.759) | (0.898) |
| Male $\times$ Rating = B | 0.171 | 0.121 | 1.497** |
| | (0.475) | (0.577) | (0.653) |
| Male $\times$ Rating = C | 0.583 | 1.508* | 1.853 |
| | (0.595) | (0.799) | (1.349) |
| Male $\times$ Rating = D | -0.163 | 0.111 | 2.020** |
| | (0.625) | (0.746) | (0.907) |
| Male $\times$ Rating = E | -0.470 | 0.375 | 0.288 |
| | (0.628) | (0.781) | (0.937) |
| Male $\times$ Rating = F | 0.464 | 0.550 | -0.064 |
| | (0.574) | (0.726) | (1.048) |
| Male $\times$ Rating = G | -0.856 | -0.220 | 0.795 |
| | (0.638) | (0.731) | (0.916) |
| Male $\times$ Rating = H | -0.596 | 0.175 | 1.585 |
| | (0.745) | (0.833) | (0.979) |
| *Duration: 60 months* | -1.009*** | -1.360*** | -1.106*** |
| | (0.161) | (0.202) | (0.246) |
| *Loan amount* | -0.049*** | -0.040*** | -0.023*** |
| | (0.003) | (0.004) | (0.005) |
| *Financial burden* | Yes | Yes | Yes |
| *Employment status* | Yes | Yes | Yes |
| *Age* | -0.015** | -0.021*** | -0.017* |
| | (0.006) | (0.008) | (0.010) |
| *Description* | 0.374*** | 0.156** | 0.327*** |
| | (0.067) | (0.074) | (0.089) |
| Place of residence | Yes | Yes | Yes |
| Loan purpose | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes |
| Pseudo-$R^2$ | 0.518 | 0.584 | 0.616 |

## Table 5.9: Two-stage estimation of Equation 5.1

The table reports results of the two-stage estimation of Equation 5.1 with dependent variable equal 1 if loan application is completely funded and 0 otherwise. Panel *A* reports results of the first-stage auxiliary probit regressions whereby loan amount and interest rate are regressed on a set of exogenous variables. Panel *B* summarizes results of the second-stage estimation. Here, variables *Loan amount* and *Interest rate* are the respective fitted values obtained from the first-stage regressions. Estimated standard errors are reported in parentheses. ***, ** and * indicate significance at 0.01, 0.05 and 0.1 levels respectively. The number of observations is 4,144.

**Panel *A*: First-stage regressions**

| | *Loan amount/250* | | *Interest rate* | |
|---|---|---|---|---|
| *Male* | 1.748** | (0.746) | -0.233*** | (0.070) |
| *Duration: 60 months* | 12.283*** | (0.774) | 0.193*** | (0.073) |
| *Rating* | | | | |
| A (reference category) | | | | |
| B | -2.087* | (1.170) | 0.658*** | (0.111) |
| C | -1.685 | (1.344) | 1.559*** | (0.127) |
| D | -4.256*** | (1.329) | 1.972*** | (0.126) |
| E | -4.316*** | (1.313) | 2.998*** | (0.124) |
| F | -2.474** | (1.261) | 3.889*** | (0.119) |
| G | -4.545*** | (1.194) | 5.271*** | (0.113) |
| H | -7.737*** | (1.313) | 6.661*** | (0.124) |
| *Financial burden* | | | | |
| low (reference category) | | | | |
| moderate | -4.414*** | (1.054) | 0.866*** | (0.100) |
| substantial | -3.805*** | (1.005) | 1.301*** | (0.095) |
| high | -7.847*** | (1.039) | 1.872*** | (0.098) |
| *Employment status* | | | | |
| Civil servant (reference category) | | | | |
| Employee | -0.573 | (1.692) | 0.490*** | (0.161) |
| Free-lancer | 15.864*** | (2.014) | 1.015*** | (0.191) |
| Managing partner | 19.867*** | (2.263) | 1.118*** | (0.215) |
| Sole proprietor | 14.184*** | (1.817) | 1.270*** | (0.173) |
| Retiree | -8.757*** | (2.108) | 1.309*** | (0.200) |
| *Age* | 0.199*** | (0.033) | -0.006** | (0.003) |
| *Description* | 2.087*** | (0.313) | -0.076*** | (0.029) |
| *Loan purpose* | | | | |
| House & garden (reference category) | | | | |
| Education & training | -2.376 | (1.901) | -0.184 | (0.181) |
| Car purchase & repairs | 0.276 | (1.170) | -0.414*** | (0.111) |
| Business loan | 7.161*** | (1.348) | -0.300** | (0.128) |
| Family & child raising | -1.226 | (1.352) | 0.154 | (0.128) |
| Special occasions | -1.932 | (2.297) | 0.151 | (0.218) |
| Health care | -6.698*** | (2.165) | -0.247 | (0.206) |
| Liquidity | 0.908 | (1.259) | -0.418*** | (0.120) |
| Vacation | -5.828*** | (2.240) | -0.455** | (0.213) |
| Hobby | 7.520 | (5.110) | 0.642 | (0.485) |
| Other/Not specified | 0.004 | (1.195) | 0.012 | (0.114) |
| Sport | 0.738 | (2.775) | -0.071 | (0.264) |
| Animals | 7.013* | (4.223) | 0.109 | (0.401) |
| Consolidate/repay debt | -0.123 | (1.262) | -0.389*** | (0.120) |
| Consumer electronics | -4.855** | (2.403) | 0.177 | (0.228) |
| *Place of residence* | | | | |
| Berlin (reference category) | | | | |
| Baden-Württemberg | 2.428 | (1.480) | 0.296** | (0.141) |
| Bayern | 4.217*** | (1.426) | -0.032 | (0.135) |
| Brandenburg | 3.673 | (2.198) | -0.059 | (0.209) |
| Bremen | 8.388** | (3.815) | 0.034 | (0.362) |
| Hamburg | 1.841 | (2.163) | 0.397* | (0.206) |
| Hessen | 0.227 | (1.610) | 0.250 | (0.153) |
| Mecklenburg-Vorpommern | 0.788 | (2.919) | 0.027 | (0.277) |
| Niedersachsen | 0.743 | (1.634) | 0.033 | (0.155) |
| Nordrhein-Westfalen | 2.201 | (1.387) | 0.198 | (0.132) |
| Rheinland-Pfalz | 1.652 | (1.907) | 0.236 | (0.181) |

(continued on the next page)

| | *Loan amount/250* | | *Interest rate* | |
|---|---|---|---|---|
| Saarland | 0.311 | (3.675) | 0.491 | (0.349) |
| Sachsen | 6.041*** | (1.984) | 0.352* | (0.188) |
| Sachsen-Anhalt | 3.169 | (2.579) | 0.434* | (0.245) |
| Schleswig-Holstein | 3.927** | (2.130) | 0.353* | (0.202) |
| Thüringen | 2.873 | (2.448) | 0.255 | (0.233) |
| *Time effects* | Yes | | Yes | |
| Adj. $R^2$ | 0.289 | | 0.674 | |

**Panel *B*: Second-stage regression**

| | *Probability of funding success* | |
|---|---|---|
| *Male* | -0.111 | (0.081) |
| *Interest rate* | 0.244** | (0.104) |
| *Duration: 60 months* | -0.500*** | (0.096) |
| *Loan amount/250* | -0.024*** | (0.005) |
| *Rating* | | |
| A (reference category) | | |
| B | -0.607*** | (0.149) |
| C | -0.627*** | (0.224) |
| D | -1.096*** | (0.264) |
| E | -1.133*** | (0.358) |
| F | -1.736*** | (0.438) |
| G | -2.264*** | (0.583) |
| H | -2.737*** | (0.732) |
| *Financial burden* | | |
| low (reference category) | | |
| moderate | 0.472*** | (0.139) |
| substantial | 0.817*** | (0.174) |
| high | 1.176*** | (0.238) |
| *Age* | -0.010*** | (0.003) |
| *Description* | 0.177*** | (0.037) |
| *Loan purpose* | | |
| House & garden (reference category) | | |
| Education & training | -0.129 | (0.202) |
| Car purchase & repairs | -0.326*** | (0.122) |
| Business loan | 0.178 | (0.160) |
| Family & child raising | -0.030 | (0.133) |
| Special occasions | -0.471** | (0.216) |
| Health care | 0.015 | (0.221) |
| Liquidity | 0.046 | (0.143) |
| Vacation | -0.154 | (0.234) |
| Hobby | -0.056 | (0.450) |
| Other/Not specified | -0.440*** | (0.113) |
| Sport | 0.254 | (0.289) |
| Animals | -0.298 | (0.342) |
| Consolidate/repay debt | -0.277** | (0.141) |
| Consumer electronics | -0.078 | (0.225) |
| *Time effects* | Yes | |
| Wald-test of exogeneity | $\chi^2$ = 2.56 | Prob = 0.277 |